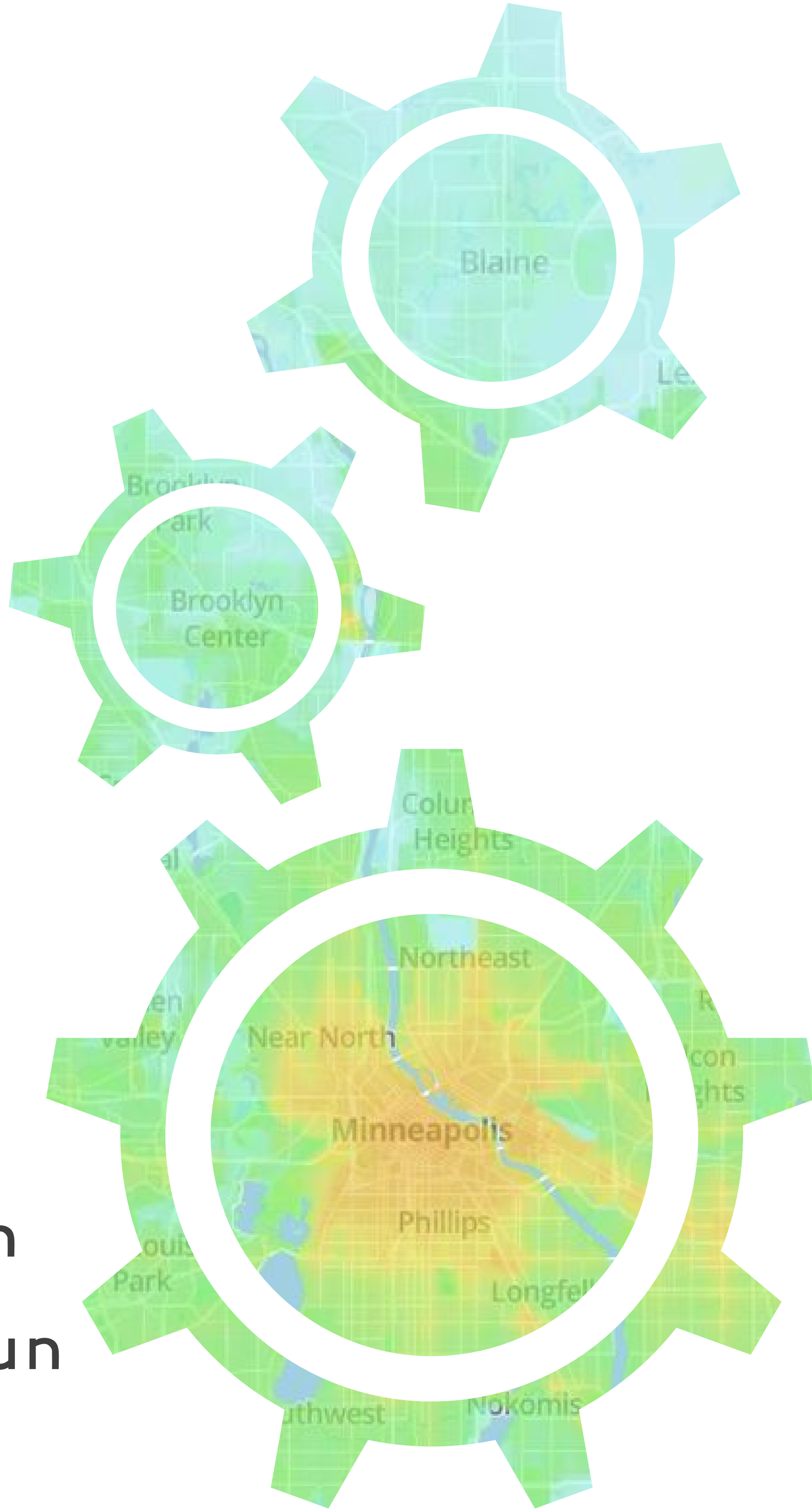
APPLICATIONS OF ACCESS



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An Introduction to Applications of Access

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Access described

From its source Latin *accedere*, the assimilated form of *ad* and *cedere*, access means "to approach." It conveys the "habit or power of getting into the presence of someone or something." The contemporary meaning differs, but has not strayed too far from the origin. Access means freedom, possession rights, and other means of benefiting from resources. It offers neither what people *will* do, nor what people *want to* do, rather what people *could* do. Transport access is a product of mobility and place and immediately relates to the transport network and the relative location of human activities and housing. However, there is still confusion among engineers and planners in differentiating access from mobility. Mobility indicates one's ability to move easily. It encompasses both speed and travel time by defining how far one can travel in a given time. Access, however, is concerned with the opportunities that can be reached in a given time.

The notion of access as a central force in transport and urban development goes back at least a century. One of the early thinkers of access was Richard M. Hurd, the President of the Lawyers Mortgage Company. In 1903, in his book, *Principles of City Land Values*, Hurd sought to determine land values and development to assess loan worthiness, with "access" as the core concept.[1] He employed access to predict which patterns of transport infrastructure and land use would most improve urban

[1] (Hurd 1903).

development. Two decades later, Robert M. Haig further expanded this notion and argued that access has the potential to provide a scientific basis for urban planning and zoning.[2] In the mid-20th century, the focus from merely describing the notion of access shifted to defining its mathematical form. One of the first studies in this regard was done by Stewart, who suggested mathematical metrics for evaluating access and reflected on its potential in land use development and planning.[3] Later, Hansen defined access as "the potential of opportunities for interactions" and presented an access measure to predict growth in metropolitan areas.[4] Contemporary access measures and applications mostly resonate with Hansen's work. But it was not until the late 20th century that the concept of access blossomed and attained a more mature definition. Scholars and planners gradually began to discern that access can go beyond theoretical research and be used normatively in planning practice.

[2] (Haig 1926, Levine 2020).

[3] (Stewart 1948).

[4] (Hansen 1959).

Wachs and Kumagai expanded the concept of access and introduced it as a social indicator and an element of life quality for policy and planning.[5] During the 1990s, research in transport and land use continued to explore the possibility of employing access in practice.[6] But the notion was not as widely adopted in practice as academics hoped. Yet, repeated conceptual and theoretical modifications gradually formed the modern definition of access and its broad application in urban planning. Advances of technology (e.g., Geographic Information Systems (GIS) and specialized spatial analysis software) in the 2000s gave rise to a plethora of possibilities for measuring access. This threw a flood of light onto this concept and led to renewed interest in scientific and practical advances for implementing access analysis.

[5] (Wachs and Kumagai 1973).

[6] (Levinson 1998).

Soon failures of the mobility-oriented infrastructure paradigm in providing solutions for the traffic congestion it purported to address, alongside its contribution to the climate change crisis, caused frustration and eventually led to the revival of applications of access in urban planning and development.[7] Technology advances have enabled researchers to generate access measures at a high spatial and temporal quality, yet, the practical implementation of access is moving at a planner's pace. Even adoption of simple access measures, such as cumulative opportunities, remains frustratingly slow.[8] We propose that a comprehensive understanding of the broad applications of access could inspire

[7] (Handy 2020).

[8] (El-Geneidy and Levinson 2021).

researchers and practitioners to consider implementing this concept in practice more often.

Through the past decades, access has been defined as the ease of reaching valued opportunities, including both life's necessities like workplaces and food stores, and its amenities, like parks and restaurants, and its measurement and application lead to mobility and land-use changes in urban planning.[9]

[9] (Levine 2020).

This definition introduces access as both a transport performance measure and an index for planning and development.[10] However, this view of access is merely the tip of the iceberg when it comes to studying its applications in transport and urban planning. In the research literature, the application of access has been associated with health impacts, economic evaluation, public transit system effectiveness, travel behavior, land use policy, urban planning and development, equity and social justice, and the built environment. Striving to reflect on the significance and comprehensiveness of access applications, we collected 19 chapters covering access research in seven main categories to illustrate the state-of-the-art of access applications along distinct dimensions of transport studies.

[10] (Ermagun 2021).

Overview of the book

Our chapters cover access research at the international, national, metropolitan, and city levels. American cities are studied in chapter 3, chapter 4, chapter 11, chapter 14, chapter 16, chapter 18, and chapter 19. International cases are assessed and compared in chapter 2 and chapter 17, while chapter 9 examines Munich, Germany and chapter 13 analyzes Jakarta, Indonesia.

Chapters are grouped into seven informal and overlapping categories:

Equity and social justice

In chapter 2, Santos and Boisjoly discuss a series of case studies that display a growing concern for transport equity. They suggest that professionals and policymakers can adopt access-based approaches to foster social inclusion through equitable transport policies. In chapter 3, Palmateer and Levinson evaluate potential measures of distributive justice based on the access to jobs provided by various modes and offer recommendations for appropriate use of each measure. In chapter 4, Borowski, Ermagun, and Levinson explore

Opportunities accumulated

In 1959, Walter Hansen borrowed the concept of potential or or opportunity for interaction to describe access to opportunities and defined "accessibility" as "the potential of opportunities for interaction."(Hansen 1959) What has come to be known as the Hansen equation (Equation 1.1) has been used to measure access to different opportunities including employment, schools, groceries, hospitals, libraries, and parks.

$$A_i = \sum_j O_j f(C_{ij}) \tag{1.1}$$

Where:

A_i : access from location i.

O_j : number of opportunities available at location j.

C_{ij} : cost of travel from i to j.

$f(C_{ij})$: impedance function.

Cumulative opportunities measures count the number of opportunities within a *travelshed*. A travelshed is equivalent to the area enclosed by an *isochrone*, and refers to an area whose boundary is a given travel time from the origin. Opportunities that can be reached within the travelshed t are weighted with a value of one, and those that cannot be reached are weighted with a value of zero as in Equation 1.2.

$$f\left(C_{ij}\right) = \begin{cases} 1\ if\ \ C_{ij} & \leq t \\ 0\ if\ \ C_{ij} & > t \end{cases} \tag{1.2}$$

the relation between transit-based job access and minority races and ethnicities, low- and middle-income households, and carless households at the block group level for the 50 most populated metropolitan areas in the United States. The analyses show that access is unevenly distributed across metropolitan regions across the US when considering various socio-demographic populations. Different metropolitan regions provide different levels of access for all investigated socio-demographic categories, whether considering racial minorities, levels of income, or car ownership.

Resilience and crisis

In chapter 5, DeWeese, Manaugh, and El-Geneidy show how access can be used as a rapid diagnostic tool to assess the potential impacts of public transport service adjustments during a public health crisis. In chapter 6, Ghorbanzadeh, Kim, Ozguven, and Horner assess the spatial access of US census population block groups to congregate and non-congregate shelters in Northwest Florida. They argue that many areas in Northwest Florida have lower access to non-congregate shelters compared to congregate shelters.

Active transport

In chapter 7, Murphy, Owen, and Levinson predict pedestrian activity using scalable and transferable predictive variables. They show that access to jobs by walking and transit, automobile traffic, and specific economic job categories (Education, Finance) are significant predictors of increased pedestrian traffic. In contrast, access to other economic job categories (Management, Utilities) significantly predict decreased pedestrian traffic. In chapter 8, Schoner and Levinson study people's navigation from place to place using the Nice Ride Minnesota bikeshare system in Minneapolis. The results indicate people prefer to use stations that do not require long detours out of the way to access. However, commuters and non-work travelers differ in how they value the walking portion of their trip and what station amenities and neighborhood features increase a station's utility. In chapter 9, Duran-Rodas, Nichols, and Büttner conducted a spatial fairness assessment to analyze which social groups are favored with active access to Urban E-commerce Infrastructure (UEI) in Munich and claim that e-commerce infrastructure benefits the cosmopolitan population, regardless of social status.

Public transport

In chapter 10, Zeng, Song, and Chen present methods and procedures to evaluate grocery store spatio-temporal access considering coupled constraints of transit schedules and store opening hours. The findings suggest that decision-makers need to consider the variations in access levels across different spatial locations, times of the day, and social groups within various living-built environments. In chapter 11, Guthrie and Fan explore

the ability of transit systems in regions to provide post-secondary education and job placement services destinations for marginalized workers. Their results provide compelling evidence for the social equity benefits of regional transit investments and the importance of integrated transit, land use, and regional public service planning.

Auto travel

In chapter 12, Huang and Levinson examine the impact of land use around the home on vehicle trip generation and identify the correlation of trips made by the same individual in the trip generation models. The results indicate that although access around the home is not found to have statistically significant effects on non-work vehicle trips, the diversity of services within 10 to 15 minutes and 15 to 20 minutes from home can help reduce the number of non-work vehicle trips. In chapter 13, Andani, Paix, Rachmat, Syabri, and Geurs describe an evaluation of the job access and spatial equity impacts of the Cipularang toll road in the Jakarta – Bandung corridor in Indonesia. The analysis reveals that the construction of the toll road has reduced travel time in the whole region by 13%, and potential job access increased by 5%.

System performance

In chapter 14, Ermagun and Levinson disentangle the impacts of financial and physical dimensions of transit service operators on net transit access. The results indicate that using the same operating expenses for both bus and train services, the bus system provides roughly 6 times more access than the train system. The bus system also operates 4 times more efficiently than the train system, providing access with the same frequency. In chapter 15, Iacono, Cao, Cui, and Levinson investigate the relation between urban access and firm agglomeration, as reflected in patterns of employment densities. They argue that urbanization effects tend to overshadow those of localization effects. These effects vary by sector, with many service-based sectors showing a stronger propensity to agglomerate than manufacturing and several "basic" sectors like agriculture, mining, and utilities. In chapter 16, Janatabadi, Tajik, and Ermagun study the spatial and temporal disparity of modal access to employment in Chicago and its nine neighborhoods. The findings alert urban planners and policymakers on the effects of travel time and space on access analysis. They also

explain how inaccurate perceptions of transit performance prevent the development of an effective and equitable transit system.

Project evaluation

In chapter 17, Stewart and Byrd evaluate how interactive tools for calculating and visualizing indicators of access to opportunities can facilitate more integrated metropolitan planning. In chapter 18, Palmateer, Ermagun, Owen, and Levinson examine the importance of service area definition when utilizing access-based evaluation in transit projects. The results indicate that the choice of transit service areas significantly impacts the value of absolute access measures. In chapter 19, Palmateer, Owen, and Ermagun use the access-based evaluation method to unpack the interaction effect of transit-oriented development and a new transit hub using the San Francisco Transbay Transit Center Development Plan project. This indicates that in areas where there already is transit service, the development of land near the transit service can have a greater impact on access levels than the improvement of connections between transit services. The book ends in chapter 20 with a review by Jin, Cheng, and Witlox of how virtual access interacts with physical access and how the interaction affects travel-access relations in the future.

Despite the classification, topics include other essential subjects; access in relation to economic development,[11] health impacts,[12] urban freight management,[13] travel demand,[14] travel behavior,[15] and technology[16] are secondary themes running through the book chapters. These 19 chapters studying cities from four continents show the spatial spread of the idea of access and suggest the variety of applications of access in different contexts.

[11] chapter 11, chapter 13, and chapter 15.

[12] chapter 5 and chapter 10.

[13] chapter 9.

[14] chapter 7 and chapter 12.

[15] chapter 8.

[16] chapter 20.

Onward

The overarching goal of this book is to provide a snapshot of the versatility of the applications of access, both in scientific research and in practice at the onset of the third decade of the 21st century. If we succeed, this book will spark reflection on the part of researchers, practitioners, and policymakers to be inspired and adopt the application of access in a broader array of research and applications.

2

Fostering Social Equity and Inclusion

Pâmmela Santos and Geneviève Boisjoly

Abstract: This chapter seeks to inspire professionals and policymakers to adopt access-based approaches to foster social inclusion through equitable transport policies. Linking access and social inclusion provides planners and decision-makers with an opportunity to address a broader variety of societal goals. Focusing on South and North America, this chapter discusses a series of case studies that display a growing concern for transport equity. Governing bodies and planners increasingly address the social dimension of transport and its role in alleviating poverty and social exclusion. Within this context, the notion of equitable access to opportunities is put forward as a key determinant, and strategies aiming at improving this access, through land use and transport planning, are developed. Measures of access to destinations are gradually incorporated in the planning documents. Yet, the related equity analyses, and their inclusion in planning processes, are still in their early stages. Exploratory rather than formal processes are implemented, which stems from an overarching goal of pushing forward the idea of equitable access to opportunities. In parallel, measures of access to opportunities are increasingly made publicly available by researchers, providing planners and researchers with an opportunity to include quantitative measures of access in their land use and transport appraisals.

Introduction

With the development of a variety of access measures that are well suited to evaluate the performance of land use and transport

Keywords: Social equity; Access indicators; Land use and transport planning; Global South; Transport equity.

networks, an increasing number of transport planning documents now include such measures, although not always in an effective manner. The access-based approach aims to capture the benefits provided to individuals by land use and transport networks, rather than focusing on travel speeds and vehicles.

Doing so provides planners and decision-makers with an opportunity to address social inclusion and equity. In 1973, Wachs and Kumagai published "Physical access as a social indicator" in which they discuss how access can be included in transport plans and evaluations to address the social component of transport.[1] The efforts that followed were mainly conceptual, given the lack of tools to quantify access to opportunities. Since the early 2000s, with increasing computational tools, data, and power, there has been a renewed interest in access measures. Researchers have sought to demonstrate the empirical links that exist between access and social exclusion and conceptualize the links through various theories of social justice.

[1] (Wachs and Kumagai 1973).

Drawing from studies looking at transport and equity from all around the world, Lucas developed a framework illustrating the relationships between transport disadvantage, social disadvantage, (in)access, and social exclusion.[2] The key relationships are presented in Figure 2.1. Lucas emphasizes that it is the combination of both transport and social disadvantages that leads to transport poverty, which in turn creates barriers to access goods and services that are essential to participate in activities in a society. Transport disadvantage relates directly to mobility components (e.g., poor public transport services, no private car, and perceptions of risks during trips), whereas social disadvantage includes individual and household characteristics such as age (children and the elderly), low income, unemployment, health issues, and poor housing. Her work highlights that physical access is a central determinant of social exclusion and that it is conditioned by a diversity of individual and contextual factors. Lucas also demonstrates how a more mobile society may exacerbate transport-related exclusionary processes and inequities.

[2] (Lucas 2012).

In line with Lucas' work, several authors have drawn on theories of justice to illustrate the relevance of considering access for more inclusive transport policies.[3] This body of literature argues that transport planners and policymakers wishing to improve equity in the distribution of transport infrastructure and services should be primarily concerned with the level of access that is provided to

[3] See (Pereira et al. 2017) for a detailed account.

Figure 2.1: Relationships between transport poverty, access, and social exclusion (inspired by (Lucas 2012))

individuals, as this is what enable individuals to meet their needs and pursue their own life plans. Since individuals inevitably have unequal opportunities in society, given internal and external constraints, they also suggest that an unequal distribution of transport benefits (prioritizing disadvantaged groups) should be considered to minimize overall inequality of opportunities.

In a nutshell, access and social inclusion are intrinsically linked. Yet, developing equity and access analyses is a significant challenge, given the wide diversity and specificity of individual needs and experiences. As such, most authors argue that transport-related social exclusion is a multi-dimensional process that encompasses spatial and social components but, is not always spatially and socially concentrated.[4] A major challenge, therefore, resides in capturing the specificity of social exclusion, while providing a level of aggregation that is helpful to evaluate land use and transport systems.

[4] (Preston and Rajé 2007).

Questions

This chapter addresses the following question:

- How do access analyses and applications consider disadvantaged groups, based on socioeconomic characteristics such as income and race, but also age and functional limitations?

It is important to mention that several efforts have also been made in Europe, although they are not discussed in this chapter.

The chapter compares and contrasts large metropolitan regions in North America (United States and Canada) and South America (Brazil and Chile). The metropolitan regions in these countries present some similarities in terms of urban sprawl and car dependency, but also important distinctions with respect to socio-spatial inequalities, urban patterns, and governance. A series of case studies are discussed, illustrating the progress and

limitations of current access-based planning approaches, with a focus on its potential contribution to social inclusion.

Methods

Place-based measures of access for equity appraisals of land use and transport systems

In the last two decades, a large body of literature has emerged to propose methods to assess transport equity using access-based indicators. The most common approach to reconcile the trade-offs between the individual nature of transport-related exclusion and the level of aggregation desired for land use and transport planning is to measure placed-based access across socioeconomic groups. In this context, place-based access is defined as the number of opportunities (e.g., jobs, healthcare services, amenities) that can be reached from a determined location using a specific mode of transport and under a specific travel time threshold. Figure 2.2 is an example of a place-based measure of access to jobs within 45 minutes of travel time by public transport in the Montréal Region. The map shows that access is much higher around locations with a high concentration of jobs and along the metro lines, highlighting the contribution of both land use and transport systems to access.

Place-based access indicators (Figure 2.2) are typically combined with socioeconomic data to assess socio-spatial disparities. The idea is to assess the differentiated level of access across socioeconomic groups. Such approaches can be used to assess the current access patterns or the effects of changes in the system. For example, measures of access to jobs and schools by public transport show how the changes in the public transport network between 2014 and 2017 in Rio de Janeiro benefited the different income groups.[5] The spatial distribution of access improvements was compared with the spatial distribution of income groups, where areas were categorized in deciles based on the average household income per capita. The authors demonstrated that low-income neighborhoods saw the lowest improvements in access, in contradiction with the aim of the official discourses surrounding transport policies. From a social equity perspective, low-income areas should be provided with higher access by public transport, to reduce transport poverty, as illustrated in Figure 2.3. As such, as social disadvantage increases, interventions should aim at reducing transport disadvantage.

[5] (Pereira et al. 2019).

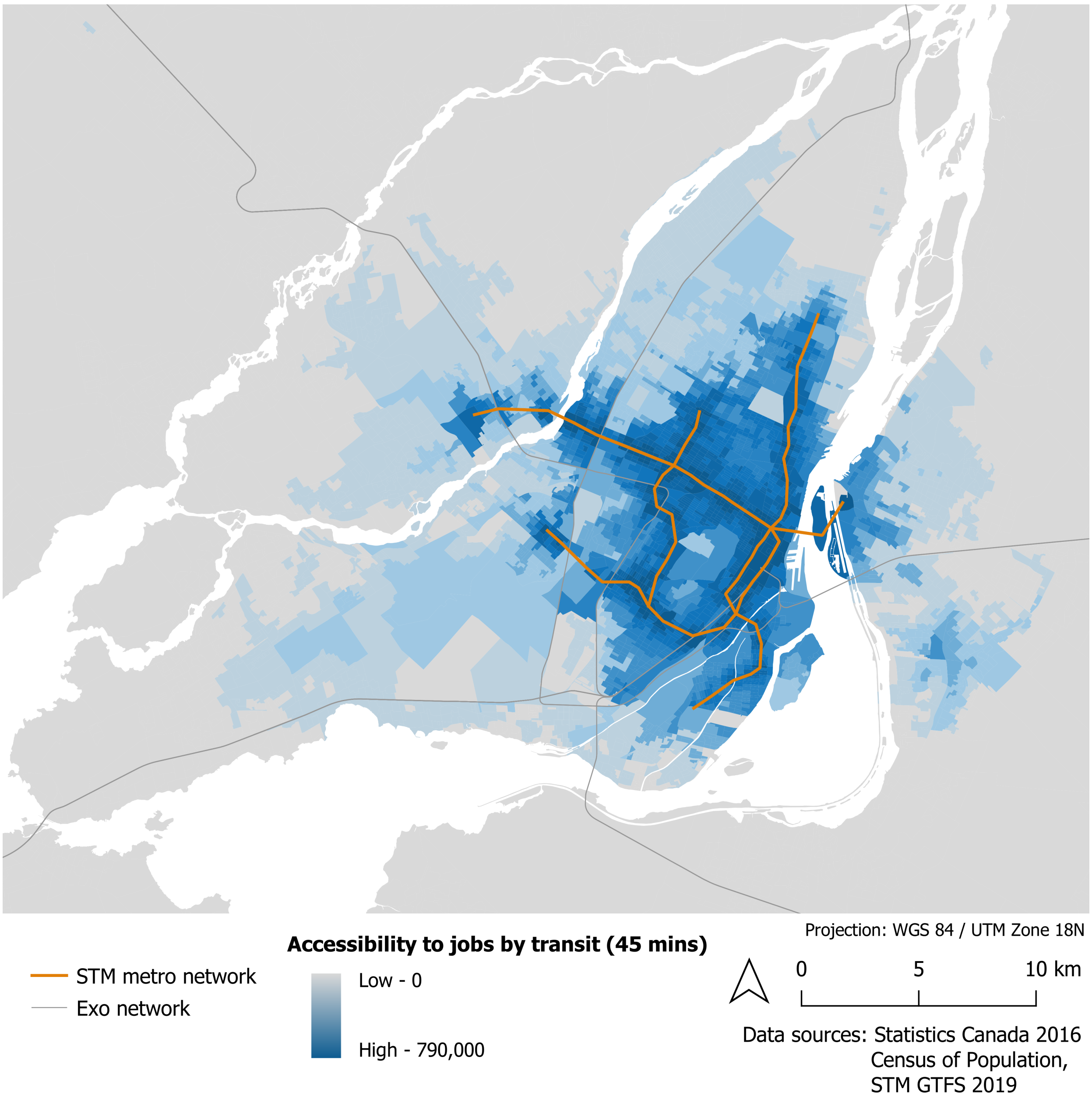


Figure 2.2: Place-based access indicators presenting the number of jobs that can be reached by public transport at 8:00 AM within 45 minutes of travel in Montreal, Canada (Author: Julian Villafuerte Diaz)

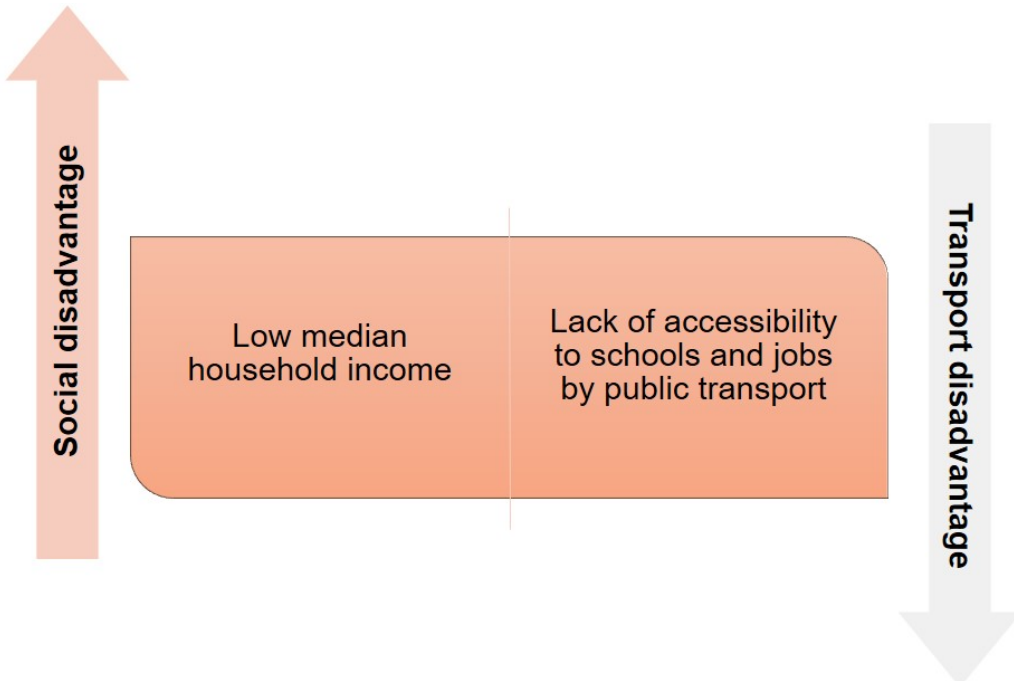


Figure 2.3: Desired direction of interventions on transport disadvantage, aiming at counterbalancing social disadvantage: Example from an equity appraisal in Rio de Janeiro

Interactions between transport and social disadvantages

Combining access indicators with socioeconomic characteristics enables researchers and planners to assess the distribution of access across socioeconomic groups. The underlying aim is to measure the cumulation of transport and social disadvantages, which together contribute to transport poverty and social exclusion, as illustrated in Figure 2.1. By measuring access and income levels, it is possible to identify neighborhoods where individuals are more likely to experience transport-related social exclusion. As such, areas concentrating a high proportion of low-income individuals (social disadvantage) and having low levels of access (transport disadvantage) are more likely to see individuals who encounter lack of access and difficulties in reaching their desired destinations. The combination of independent access and socioeconomic indicators is commonly used in research and planning given its ease of operationalization and interpretation. Nonetheless, this approach is limited in capturing the interactions between transport and social disadvantages. The access indicators described above are solely based on land use and transport factors (transport-oriented access),

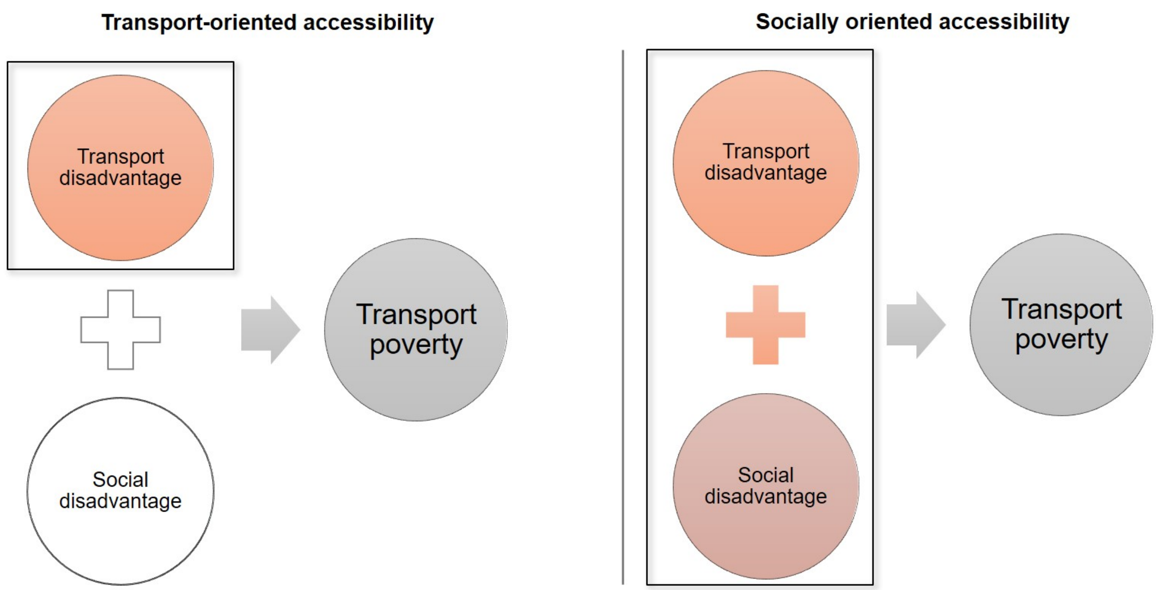


Figure 2.4: Components of transport-oriented and socially-oriented access

regardless of the individual characteristics. In other words, under this approach, indicators of transport disadvantage are measured independently from social disadvantage, as highlighted in Figure 2.4.

Another way to measure access, which is referred to here as socially-oriented access, is to directly account for these interactions when measuring access (see Figure 2.4). Social disadvantage characteristics are thus considered directly in the calculation of access. To do so, distinct access indicators can be generated for distinct population groups, to account for differentiated needs and abilities. A common approach is to segment measures of access by type of jobs or destinations, thereby combining transport and social characteristics into one measure. For example, several studies have refined their measures of access to jobs by considering the job sector and education level associated with the job. This enables tailoring the access measures to the destinations that matter to the workers.[6] Another approach is to generate differentiated travel time and monetary budgets to account for discrepancies in households' constraints and preferences.[7] This approach more closely reflects the level of access experienced by the different households. It is important to mention that while every individual has distinct characteristics, and therefore experiences of access, some level of

[6] For example, (Foth et al. 2013) measured the access to low-skilled jobs only compared to the level of access to all jobs.

[7] (Bocarejo and Oviedo 2012).

aggregation is nonetheless required to generate indicators that can be used directly in land use and transport plan evaluations. Most access analyses, in research but also in planning, focus on a few specific socioeconomic characteristics, mainly income, and to a lesser extent ethnicity, race, or immigration status. For example, in Latin America, most studies focus on low-income individuals with little attention to gender and age.[8] Yet, while these are rarely considered in access studies, they have a significant influence on the level of access experienced by individuals. Research has demonstrated that the barriers and preferences experienced by elderly people and women can significantly differ from the ones that are typically considered, namely with respect to safety and comfort. As for children (and their parents), they are typically more sensitive to traffic levels around public transport infrastructure.

[8] (Vecchio et al. 2020).

With respect to the elderly and individuals with functional limitations, which have received more attention than children and gender, most studies focus on access to public transport services, rather than to destinations. Nonetheless, a few studies have developed socially-oriented measures of access by public transport that consider the mobility barriers that are imposed to individuals with a functional limitation. A recent study compared the level of access to jobs, by public transport, for individuals with and without a physical disability,[9] accounting for whether the public transport infrastructure (stops, stations and vehicles) were accessible to individuals in a wheelchair. Another study additionally accounted for reduced walking speeds and distances.[10]

[9] (Grisé et al. 2019).

[10] (Oh et al. 2017).

Another important component to develop socially meaningful measures is the temporal dimension of access. The case of low-skilled workers is a telling example of how transport and social disadvantages can interact with one another to contribute to transport poverty and inaccess. In several metropolitan regions, low-skilled workers are more likely to work outside peak hours and to rely on public transport, and therefore experience difficulties in terms of accessing their work locations. It is the lack of public transport services outside peak hours together with the fact that these workers are more likely to work outside peak hours that may lead to access barriers. When a single access indicator is developed for the whole population (either number of jobs accessible at peak hours or average number of jobs accessible per hour throughout the day), as commonly done, the transport poverty resulting from this interaction is not captured. In fact, access is measured regardless of

the abilities, needs and constraints of individuals, although they have an important impact on the experienced level of access.

Findings

US federal laws and requirements on transport and equity

The lack of geographic access to employment was identified as a major cause of social unrest in the late 1960s. The post-war changes in urban structure and the associated car-oriented development brought new barriers to access employment opportunities, which resulted in high unemployment rates among central city, low-income residents, largely black individuals. Several riots took place at these times in large urban centres to protest the lack of employment. This gave rise to the idea that unemployment could be explained by land use and transport factors, in addition to the individual factors such as education. A few studies explaining and theorizing the links between social inclusion and access followed. These studies remained mainly conceptual, with little operationalization of the concept.

In the late 1990s beginning of the 2000s, there was a renewed interest among researchers for measuring access via various modes of transport, largely due to new computational resources and opportunities. These efforts led to the creation of the Accessibility Observatory at the University of Minnesota, which built on an Access Across America study that was launched in 2004. The Accessibility Observatory now publishes access metrics for the 50 largest areas in the US for a variety of modes (car, public transport, walking, and cycling), and has been doing so since 2013. This well-known Access Across America initiative is funded by a group of State Departments of Transportation.[11]

[11] (Owen and Levinson 2014). These data are used in an exploration of equity in chapter 4 and chapter 3, and in an exploration of performance in chapter 14 and chapter 16.

In parallel with this initiative, the term access was incorporated in the federal guidance for the development, by the Metropolitan Planning Organizations (MPO), of regional transport plans (RTP). In line with the Transportation Equity Act for the 21st century established in 1998, the subsequent acts (MAP-21, FAST Act) required MPOs to "increase access and mobility of people and freight" as one of their eight planning factors. It is important to mention that since the term access was used in a vague way, it gave rise to a diversity of interpretations and approaches, several of which do not actually address the ease of reaching destinations. In

addition to the planning requirements, the federal Department of Transportation incorporated an Environmental Justice criterion for the development of regional transport plans, requiring planning organizations to demonstrate that their plan does not have disproportionate adverse impacts on vulnerable population groups. Therefore, equity concerns ought to be addressed by MPOs.

US regional transport plans: access and environmental justice

Taken together, the environmental justice and access requirements as well as the progress made in research led to several plans developing access-based equity analyses. Most access analyses found in RTP relate to environmental justice assessments, where the relative levels of access to destinations, by a variety of modes, is investigated across socioeconomic groups. According to environmental justice requirements, MPOs are to demonstrate that the plan does not have disproportionate negative impacts on vulnerable populations. A variety of destinations are included, namely employment, services, parks, schools, libraries, grocery stores, and hospitals. A study conducted for the Brookings Institution found that seven out of the 18 plans in the US included access metrics in their environmental justice assessment.[12]

[12] See for example Boston Region Metropolitan Planning Organization (Bocarejo and Oviedo 2012).

The consideration of access to destinations to assess social equity demonstrates how the idea that transport plays a key role for social inclusion is slowly making its way into planning. However, it is important to note that in most cases, the use of access indicators appear to be limited to meeting the environmental justice requirements, with little influence or comprehensive inclusion in the plan. Nonetheless, this allows planners, decision-makers, population, and advocacy groups to visualize the socio-spatial distribution of land use and transport systems.

Montréal: A diversity of initiatives to push access, and equity forward

In the Montréal Metropolitan region, in the last decade, several initiatives have been undertaken by the City of Montréal and the regional transport planning authority[13] to bring access and equity concerns into the transport planning and policy realms. These initiatives demonstrate an increasing interest in the social dimension of transport as well as the relevance of access indicators

[13] (Authorité Régionale de transport métropolitain (ARTM) 2020).

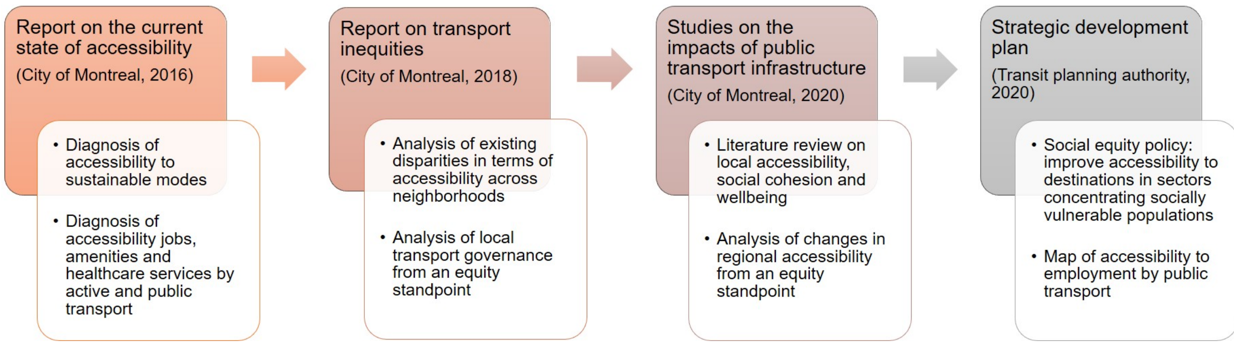


Figure 2.5: Recent initiatives considering equity and access in Montréal, Canada

to assess transport plans from a general and from an equity standpoint. These are summarized in Figure 2.5.

Whereas the 2008 Transport Plan launched by the City of Montréal did not directly address access to destinations, the City commissioned, in 2016, a specific study on access to support the revision of the transport plan. The aim of the study, conducted by the Transportation Research Group at McGill University, was to specifically assess the spatial distribution of access to sustainable modes and to destinations by active and public transport. This provided the City with a first quantitative portrait of access across the region. Two years later, the City launched a series of studies on transport equity, where access was identified as a key dimension of social equity. The first mandate was to provide a portrait of Montréal's neighborhoods in terms of mobility, access, and equity. A review of the existing literature critically assessed the current planning practices to understand how transport inequities are considered by planning authorities.[14] The existing disparities in terms of access were also reviewed based on existing studies. Important socioeconomic and spatial disparities in terms of access to jobs and grocery stores were thereby highlighted. More recently, the potential impacts of new public transport infrastructure were explored from the viewpoint of local and regional access. Two distinct studies were launched by the City with a clear focus on access. The first one aimed at understanding the impacts of massive public transport infrastructure on the social dynamics and local access of neighborhoods located along such infrastructure. Key elements that were investigated are the barriers to local access (mainly by active modes) and their negative impacts on social inclusion and well-being. The second study specifically assessed the

[14] (Paulhiac et al. 2018).

impacts in terms of regional access by public transport across the territory and across socioeconomic groups. In line with this, the Montréal regional transport planning authority (ARTM) recently included an access criterion in their strategic development plan with a concern for vulnerable population groups.[15] Within their social equity policy, the stated aim is to improve access to destinations in sectors concentrating socially vulnerable populations. A map of access to employment by public transport is provided, thereby illustrating the influence of high-performance public transport systems as well as density of jobs and services on access.

[15] (Authorité Régionale de transport métropolitain (ARTM) 2020).

Overall, we see a clear trend among planners in Montréal in the last five years to include access indicators in their planning tools and document in an effort to address the social dimension of transport. Although it is not yet implemented in the official planning practices and discourses, it is visibly included in several analyses conducted by the City and the ARTM.

Toronto: A well-established concern for access and equity

In the case of Toronto, the idea of access and equity has been consistently put forward by Metrolinx, the transport planning authority of the region, since the release of their transport plan, The Big Move, in 2008.[16] Figure 2.6 summarizes how access and equity have been considered in the various planning documents throughout the years. The Big Move falls within the broader development goal of the region which seeks to improve access to jobs, housing and services via a diversity of modes. To achieve this overarching goal, the first objectives specifically aim to increase access to destinations and emphasize the diversity of means, ability and income levels as well as the specific needs of children, seniors and individual with special needs. In terms of action and indicators though, the focus is mainly on access to fast and efficient transit services.

[16] (Metrolinx 2008).

In the 2016 discussion paper, equity and access are stated together as a main goal with the objectives of offering affordable access to destinations by public transport as well as transit infrastructure, services and technologies that are accessible to all users.[17] Maps and tables of access to labour force and jobs by public transport are presented for varying travel time thresholds, providing quantitative and visual indicators related to the objectives. Distinctions are made between residents in Downtown

[17] (Metrolinx 2016b).

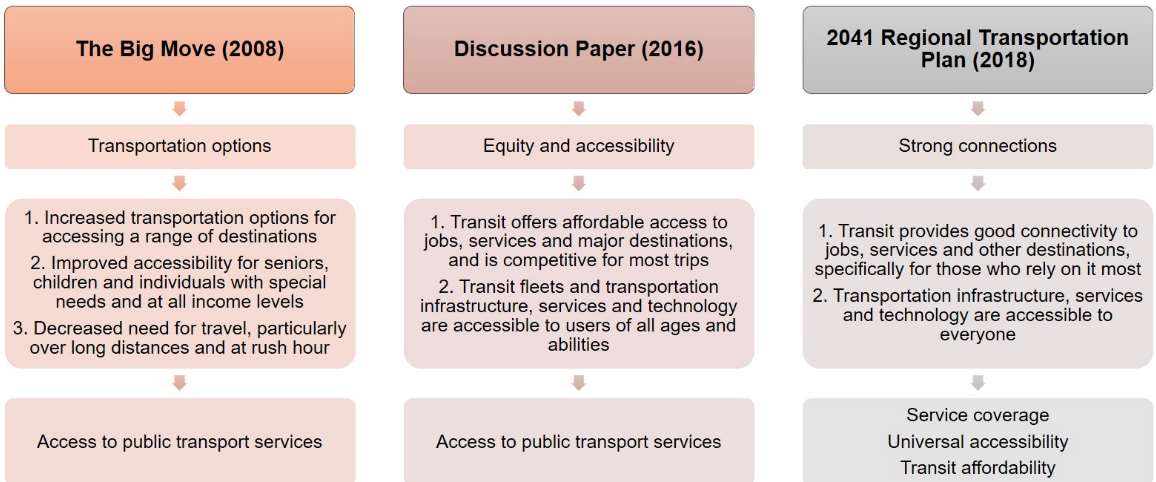


Figure 2.6: Access and equity goals and indicators included in recent planning documents in Toronto, Canada

Toronto, the City of Toronto, and the greater metropolitan region to provide some spatial equity insights. With respect to vulnerable populations, the analysis is limited to access to public transport.

The most recent plan released in 2018 states that access to jobs by public transport is considered in their scenario assessments.[18] Interestingly, specific indicators of access to jobs by public transport (within 60 minutes) are included in the scenario assessment related to the development frequent rapid transit network. These indicators are not linked with equity components; equity indicators are discussed distinctly, including service coverage, universal access and transit affordability.

[18] (Metrolinx 2016a).

Most recently, Metrolinx commissioned a report exploring transit equity through access measures.[19] Namely, the report identifies the relationship between transit access and income levels. The report demonstrates that low-income individuals are typically characterized by levels of access by transit above average, yet, a significant number of them are located in areas with very low levels of access. The report allows identifying areas with low access and a high concentration of low-income households, and also highlights the impacts of low access among low-income households in terms of activity participation.

[19] (Farber and Allen 2019).

To conclude, access and equity are recurrently discussed in the official planning documents in the region of Toronto. Although it is unclear the extent to which equity analyses are guided by access-to-destination indicators, there is a visible interest for the questions of

equity and access. The relationship between access and equity has recently been highlighted by planners.

Brazil: Towards the quantification of access to support equitable transport policies

In Latin America, Brazil is a leading example in terms of access research and applications, and transport equity is increasingly put forward. In terms of equity, a series of laws and policies promote social inclusion through transport. For example, free public transport fares were established for the elderly and disabled populations.[20]. The social inclusion of these groups through free fares sought to promote access to essential services, such as health care systems. Another measure of social inclusion through transport was the free tariff for students from public and low-income schools, aimed at improving access to education in several cities in the country.

However, much remains to be done to ensure equitable access to opportunities for marginalized groups through transport policies and planning. As such, the important socio-spatial segregation and the uneven distribution of land use and transport systems lead to important disparities in terms of access, as recently highlighted by the Institute of Applied Economic Research (IPEA). IPEA developed a project entitled "Access to Opportunities."[21] The main components are summarized in Figure 2.7. The objective is to annually estimate the population's access to job opportunities as well as health and education services. The project aims to create an open database on the conditions of urban access in Brazilian cities, which can be used by planners, researchers, and the civil society in the planning and evaluation of urban public policies, and transport and land use systems. The study includes estimates of access by active modes of transport (walking and cycling) for the 20 most populous cities in the country and by public transport for seven large municipalities (São Paulo, Rio de Janeiro, Belo Horizonte, Recife, Fortaleza, Porto Alegre, and Curitiba), based on data availability. Two types of indicators were calculated for the study:

- Minimum time: the minimum time it takes to the nearest opportunity.
- Cumulative opportunities measure: the total number of opportunities within a maximum travel time.[22]

[20] (Law No. 8,899, 1994; Law No. 10,741, 2003).

[21] (Instituto de Pesquisa Economica Aplicada (IPEA) 2020).

[22] See chapter 1 in this volume.

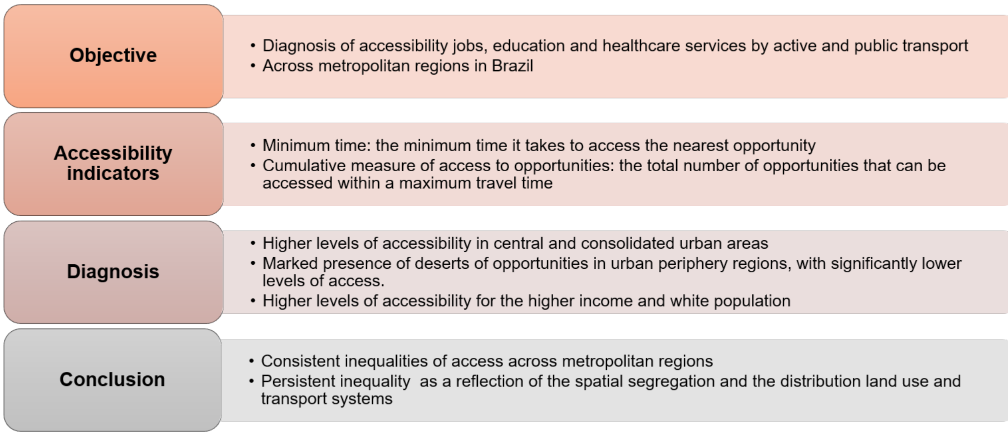


Figure 2.7: Key components of the Access to Opportunities initiative and report from the IPEA in Brazil

The indicators were then used to measure the ease with which people from different areas of the cities and from different socioeconomic groups (considering income levels and race) can access opportunities.

The first part of the study, released in 2019, highlights similar access trends across cities: a higher level of access in central and consolidated urban areas, and a more marked presence of deserts of opportunities in urban periphery regions, with significantly lower levels of access. These inequalities are also manifested by colour or race. The white population has, on average, more access to opportunities than the black population in all the cities studied, regardless of the mode of transport. The same patterns are present across income groups where lower-income households exhibiting lower levels of access to opportunities. This persistent inequality in Brazilian cities is a cause and, at the same time, a reflection of spatial segregation and structural issues generated by the uneven spatial distribution of the transport system, infrastructure, and urban development. The project aims to alert urban planners of the importance of considering access to destinations and opportunities in the preparation of urban mobility plans.

From a planning perspective, various equity and access considerations are discussed at the national and local levels, as illustrated in Figure 2.8. The National Urban Mobility Policy,[23]. sets guidelines that Brazilian cities should consider in their master plans and urban mobility plans. The policy aims at improving access to public services, via the right to equity in citizens' access to public

[23] (Law 12.587, 2012).

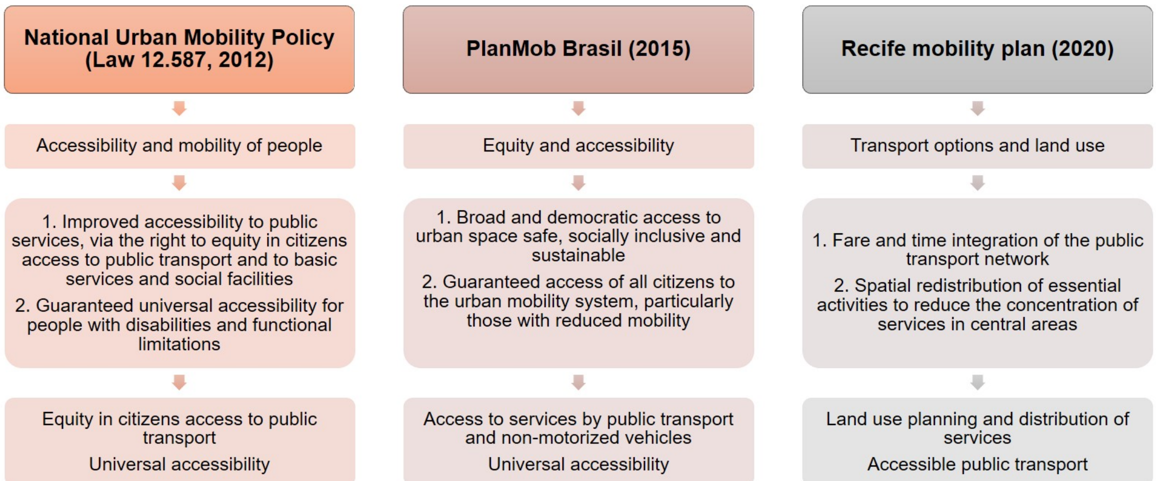


Figure 2.8: Objectives and indicators of access and equity within the planning structure of Brazil and Recife

transport and to basic services and social facilities. It also establishes the guarantee of universal access for people with disabilities and functional limitations. In parallel, the Ministry of Cities has prepared a reference document for the preparation of mobility plans in Brazil, PlanMob. This document also points out the importance of planning urban mobility considering that transport systems are essential to guarantee access to opportunities.

Through the guidelines established by the national urban mobility policy and PlanMob, some Brazilian cities have formulated or are in the process of formulating municipal mobility plans. As an example, the city of Recife, located in northeast Brazil, is developing an urban mobility plan that will incorporate, update, and revise the planning established for the municipality based on other existing plans, such as the Municipal Development Master Plan released in 2008, the 2011 Master Plan for Transport and Mobility of Recife, and the 2014 Master Plan for Cycling of the Metropolitan Region of Recife. The objective of Recife's new urban mobility plan is to promote the mobility of people, promote universal access, reduce situations of isolation and provide access to health services, education, leisure, and opportunities for work and income. As such, the plan emphasizes the importance of access to opportunities for marginalized groups, in order to meet the requirements of the national urban mobility policy.

In an analysis carried out to elaborate the mobility plan for the city of Recife,[24] it was observed that the density of the offer of

[24] (Instituto de Cidade Pelopidas Silveira (ICPS) 2020).

services and public transport is inversely proportional to income, that is, the places concentrating households with a higher income have a higher concentration of services and public transport offer. Conversely, areas where the population has a lower income exhibit a greater shortage of services and public transport. Considering this analysis, the new mobility plan foresees the need to plan transport and land use in order to guarantee greater access, through public transport, to services and opportunities for the low-income population.

Measures such as expanding the public transport network through tariff and time integration are considered essential to reduce the cost of using public transport. The planning of land use and occupation, redistributing essential activities, and reducing the concentration of services in central areas, is also a tool put forward in the mobility plan, with a focus on access to services for people from peripheral regions. The plan also aims to establish an organization of public transport lines and corridors, to better connect people to opportunities and services. Yet, there are no direct measures of access to destinations by public and active transport. Including such measures, as the ones developed by IPEA for example could help planners quantify and communicate the impacts of various strategies on equity of access.

Chile: Building on transit oriented development (TOD) to foster inclusive access

Still in Latin America, access to opportunities has also proved to be a problem in other metropolitan regions. According to the Organization for Economy, Cooperation and Development,[25] Chile is the second most unequal country of all 37 member countries, with a huge income gap, and transport is an area where these disparities are increasingly visible. The cost of public transport has a greater weight on low-income household, which, in itself, entails restrictions on accessing opportunities.

[25] (OECD 2019).

In this context, the City of Santiago, in 2019, developed an urban mobility plan for 2019 to 2029 that considers social equity as one of the pillars of city planning.[26] Institute for Transportation and Development Policy (ITDP), which promotes the right to access opportunities in cities of the Global South, produced TOD standards to support the development of more sustainable and equitable cities. Equity is at the forefront of their mission and

[26] (Institute for Transportation and Development Policy 2020).

underlies their conceptualization of TODs. As presented below, ITDP emphasizes an inclusive access to opportunities in their presentation of TOD:

> [TOD] means inclusive access for all to the city's neighborhoods and opportunities, through the healthiest combination of means of transport, with the lowest financial and environmental cost and with maximum resilience to disturbing events. It is an element to think about a sustainable and equitable future, with shared prosperity and civil peace in the cities.[27]

[27] (Institute for Transportation and Development Policy 2020).

Following this approach, the plan of the City of Santiago foresees reducing social differences, inequalities and territorial fragmentation in the city by promoting access to the benefits and opportunities of the urban space through mobility. To achieve the objective, the mobility plan of the Chilean capital defined some guidelines, such as making the city territorially equitable, promoting the creation of new opportunities amid an ecosystem of innovation, entrepreneurship and circular economy at the regional level. While no clear access indicators are presented, the plan addresses mixed land use as a measure to reduce inequality in access. The aim is to promote a more democratic land use that will contribute to reducing the distance and travel time to reach opportunity through active and public transport. The mobility plan's concern with equity also focuses on universal access by establishing fundamental principles, including access and universal design. The plan considers that since the beginning of transport and urbanism projects, access for all people must be considered in accordance with the universal access criteria.

Overall, we see that equity of access is an increasing concern, particularly in Latin America where important income disparities and socio-spatial segregation are present. access indicators are not yet integrated in plans, but planning and research initiatives such as the one by the IPEA and by the ITDP provide planners, policymakers and the civil society with a unique opportunity to quantify the socio-spatial distribution of land use and transport systems and communicate their results.

Across the world: Benchmarking equitable access

The global research organization, World Resources Institute (WRI), focuses on helping cities in rapidly urbanizing regions to change their development trajectories as demand for infrastructure and

services increases. A series of research articles and case studies examined whether access to key urban services and infrastructure is equitably distributed in urban areas. Among these studies, a report entitled "Towards a More Equal City – From Mobility to Access for All: Expanding Urban Transportation Choices in the Global South" analyzes what cities can do to change the trajectory of the urban transport sector in order to provide more equitable access the opportunities.[28]

[28] (WRI 2019).

The report features the cities of Johannesburg and Mexico City, with case studies illustrating the transport problems faced by marginalized groups. Using access to jobs and opportunities as an indicator (number of opportunities that can be reached in 60 minutes), and analyzing variables such as travel costs and public transport options, the study estimates that 42% of Johannesburg residents and 56% of Mexico City residents are not served in terms of their ability to reach workplaces. The study divides marginalized groups into two categories: people with low access and low mobility, such as city dwellers who rely on walking and cycling and for which most trips are completely inaccessible from an economic point of view; and people with low access, but with mobility, who spend above average amounts of time and money on travel, up to 35% of income. This second group, who depends mostly on car or public transport, is usually located in peripheral suburbs far from economic opportunities.

Given the above, the study points out some potential interventions to mitigate the problem of access to opportunities. To this end, the study emphasizes the need to develop complete, democratic and safe street networks and to increase the financing available for transport. It also points out the inequities between car owners and non-car owners and suggests charging users for the use of individual transport. Together with significant investments in transport systems, urban design, the implantation of well-located popular housing and more accessible environments on foot and for mixed use are presented as means to meet future needs in a more equitable and sustainable manner, as done by the cities of Johannesburg and Bogotá.

Conclusions

Focusing on South and North America, this chapter discussed a series of case studies that display a growing concern for transport

equity. Across the countries and metropolitan regions considered, governing bodies and planners increasingly address the social dimension of transport and its role in alleviating poverty and social exclusion. Within this context, the notion of equitable access to opportunities is put forward as a key determinant, and strategies aiming at improving this access, through land use and transport planning, are developed. As such, equity and access are generally discussed jointly and emphasized in policy and planning documents.

Overall, measures of access to destinations are gradually incorporated in the planning documents of the metropolitan regions that have been discussed in this chapter. In several cases, the planning authorities are concerned with the relationship between socioeconomic characteristics, mainly income, and the levels of access by public and active transport. It is possible to observe that the related analyses, and their inclusion in planning processes, are still in their early stages. As such, there does not seem to be a consistent and formalized approach. It rather appears to be an exploratory process which stems from an overarching goal of pushing forward the idea of equitable access to opportunities.

In parallel, researchers have proposed access-based approaches to evaluate land use and transport plans from an equity perspective. Measures of access to opportunities are increasingly made publicly available, with initiatives such as the ones developed by IPEA, in Brazil, and the Access Observatory, in the US. The availability of these data provides planners and researchers with an opportunity to include quantitative measures of access in their land use and transport appraisals.

Next

There is no question that important progress has been made, both in research and planning, to consider social equity in land use and transport planning, through the lens of access. More efforts are nonetheless required to further support equitable land use and transport systems.

First, it is essential to expand and refine access measures (which typically focus on income and ethnicity) to address broader social concerns, namely with respect to age, gender, and functional limitations as well as non-work destinations. In line with this, further studies should aim at understanding the determinants of

access across different population groups to develop various access measures that reflect the diversity of needs and experiences. As such, the perceptions and needs of individuals should be directly investigated, for example through surveys. The direct interactions between social disadvantage and transport disadvantage also require more consideration, namely through qualitative studies.

Second, planning agencies could build more directly on access measures to quantify, evaluate, and communicate the benefits and shortcomings of their planning policies and strategies.[29] To support that, more efforts are required to understand the needs and constraints of planning agencies. It is essential to understand how access tools and indicators can help them develop and communicate policies and strategies. A closer collaboration between researchers and planners could help bridge the gap between research developments and planning applications.

[29] See chapter 17 for a discussion of interactive planning strategies.

Finally, a key question to be investigated relates to the barriers and opportunities for integrated land use and transport planning. Access measures and planning approaches can reach their full potential only if they support joint land use and transport strategies.

3
Justice, Exclusion, and Equity: An Analysis of 48 US Metropolitan Areas

Chelsey Palmateer and David Levinson

Abstract: This chapter intends to inform recommendations for appropriate use of measures of the justice of transport services. Injustice in transport services experienced by disadvantaged demographic groups account for much of these groups' social exclusion. There is little agreement in the field about what theoretical foundation should be the basis of measures of the justice of transport services, limiting the ability of transport professionals to remedy the issues. Accordingly, there is a need for an improved measure of the justice of the distribution of transport services, which relates to the effectiveness of transport services for all members of disadvantaged groups rather than for only segregated members of these disadvantaged groups. To this end potential measures of distributive justice, based on the access to jobs provided by various modes, are evaluated in 48 of the top 50 largest metropolitan areas in the United States.

Introduction

Injustice in transport services experienced by disadvantaged demographic groups account for much of their social exclusion.[1] However, there is little agreement in the field about what theoretical foundation should be the basis of measures of the justice of transport services, limiting the ability of transport professionals to remedy the issues. Outside of academia, many attempts to quantify

Keywords: Distributive justice; Equity; Access; Transport

[1] (Frank 2000, Preston and Rajé 2007, Verbich 2016).

justice in transport projects and systems rely on proximity to concentrations of disadvantaged demographic groups. As a result, decisions based on this type of quantification exclude consideration of members of disadvantaged groups who do not live in close proximity to one another and additionally fail to indicate the effectiveness of the provided transport services.

Accordingly, there is a need for an improved measure of the justice of the distribution of transport services that relates to the effectiveness of transport services for all members of disadvantaged groups rather than for only segregated members of these disadvantaged groups. An effort to better understand the implications of each of the potential theoretical foundations of the justice measure is necessary.

Questions

This chapter aims to inform recommendations for appropriate use of each measure, based on existing transport policies regarding justice in the provision of transport services, and addresses the following questions:

- Is there an access to opportunities gap between disadvantaged and advantaged population?

- What is an appropriate use of different measures of distributive justice?

Potential measures of distributive justice, based on the access to jobs provided by various modes, are evaluated in 48 of the top 50 largest metropolitan areas in the United States. In this context, access is the ability of system users to reach desirable destinations, such as jobs and groceries with a given travel mode. Access is a direct measure of transport services and can account for individuals in areas with concentrations of their demographic groups as well as those living outside of such areas of concentration. These potential measures of distributive justice are regressed on combinations of the population of the metropolitan area, the density of those populations, the land area of the metropolitan area, and indices of segregation for disadvantaged populations.

Methods

Distributive Justice: A Brief Review of Four Theoretical Concepts

There are many theoretical foundations of justice, as a result any discussion of justice must involve multiple competing concepts. The analysis that follows is limited to four concepts of distributive justice commonly found in the literature: absolute or minimum need, equality of opportunity, the maximin theory of justice, and relative need. A brief overview of each of these is included below. These concepts can be organized in a variety of ways, but in this chapter the focus starts with the simplest concept and increases in complexity based on the number of variables under consideration.

ABSOLUTE NEED. The simplest concept of distributive justice is that of absolute or minimum need. This version of distributive justice focuses on the provision of a basic minimum allocation to all individuals. The concept is founded on the idea that there are minimal resources to which everyone is entitled. For example, individuals are entitled to the resources needed to survive, such as access to fresh water.[2] However, it is difficult to define a set minimum allocation of resources, because society tends to define the minimum acceptable level of allocation relative to the general abundance of resources. Greenburg discusses the tendency for abundance to shift the focus from providing a minimum for survival to providing for enough to enjoy a meaningful life within a society.[3]

[2] (Deutsch 1975, Grand 1984).

[3] (Greenberg 1981).

As it relates to transport services and the provision of access to jobs, a basic minimum allocation could be seen as a set number of jobs within a certain time frame. Unfortunately, an obvious and logical choice in the number of jobs that individuals should be able to reach in a given time frame is not readily available. Consider the case of a farmer, living in a rural area. Arguably, the farmer has a job which may very well be the only job opportunity for miles. Yet, the farmer is able to support his needs. As an alternate example consider a person living in a large city. This potential worker likely could reach thousands of jobs in a reasonable time frame, but his neighbors and many others could also reach the same jobs. As such the individual must compete for nearby jobs. Although numerous studies have shown that individuals budget their travel time, and that average commute times have remained similar through time, it

is commonly recognized that some individuals are willing to spend more time commuting for a variety of reasons. Furthermore, recent decades have seen the popularization of telecommuting, allowing or requiring individuals to opt to work from home, especially since COVID-19. As such any definition of a minimum allocation of job access is arbitrary. The definition can still be useful.

In addition, a more in-depth analysis would also take into account competition for jobs. This chapter considers a potential measure which accounts for competition: a ratio of the individual's access to jobs over the individual's access to other potential workers, within a time frame that would fit in a standard time budget for travel to work.[4] The equations for the ratio, described as the opportunity level at a threshold and location, as shown in Table 3.1, under the heading *Minimum Allocation: Absolute Need*. Note, this equation is based on the assumption that every individual at a location has the same access to jobs and competing workers.

[4] (Zahavi 1974).

Equality of Opportunity. Equality of opportunity is a slightly more complex concept of distributive justice. This concept has been largely developed by Peter Westen, and is founded on the idea that opportunity is a relationship between three factors: an individual, a goal, and any obstacles between the individual and the goal. Note that if there are any obstacles which the individual cannot surmount, then there is not an opportunity to achieve the goal. Some of these obstacles may not be related to the goal, but rather based on hierarchical or caste-based discriminatory practices. These obstacles are hereafter referred to as unrelated obstacles. In order to achieve equality of opportunity individuals wishing to achieve the same goals would face similar obstacles, and none of those obstacles would be unrelated or insurmountable.[5]

[5] (Westen 1985).

As it relates to transport services and the provision of access to jobs, representative groups of individuals based on such factors as income, race, ethnicity, age, religion, and gender should have the same opportunity to obtain work based on their skills. By this logic, the opportunity level of an individual defined for minimum allocation above can be averaged within representative groups to determine if equality of opportunity exists between members of different groups.[6] Distributive justice would be achieved if the opportunity level at a threshold was equal between groups, or if there were no statistically significant difference between the opportunity levels for the various groups. The equation for the

[6] See chapter 4 and (Ermagun and Tilahun 2020).

person-weighted opportunity level of a representative group is shown in Table 3.1, under the heading *Equality of Opportunity*.

MAXIMIN THEORY OF JUSTICE. The maximin theory of justice, developed by John Rawls, allows for the possibility of justice in a distribution without direct equality. Rawls proposes two principles of justice, with the requirement that the first principle be completely satisfied before the second principle is considered:

1. "Each person is to have an equal right to the most extensive scheme of equal basic liberties compatible with a similar scheme of liberties for others."[7]

[7] (Rawls 2009).

2. "Social and economic inequalities are to be arranged so that they are both (a) to the greatest expected benefit of the least advantaged and (b) attached to offices and positions open to all under conditions of fair equality of opportunity."[8]

[8] (Rawls 2009).

Applied to transport we interpret Rawls to mean that the higher the level of benefit, in this case access to jobs, provided to the group with the least benefit, the more equitable a transport system is. Equations for determining the level of access for representative groups at a threshold and overall are shown in Table 3.1 under the heading *Maximin Theory of Justice*.

RELATIVE NEED. The most complex form of distributive justice explored in this chapter focuses on distributing resources based on the relative need of the recipients. In many studies of the distributive justice of transport networks,[9] the evaluation of the gap between transit and automobile access is explored.[10] The concern is for individuals without access to an automobile and how their access compares to those who do have access to an automobile.

[9] See e.g., Benenson et al. (2010).

[10] See chapter 16 in this volume.

One way to calculate this is to find the net access within a threshold available via automobile, to see how much of an advantage users obtain if they can afford a car, over those who cannot. Similarly, it is also possible to find the net access available within a threshold via transit, to see how much of an advantage users obtain if they can afford transit, over those who cannot. However, this is a simplification. Alternatively, the gap could be calculated as the difference between the access levels of the automobile owners representative group and the transit owners representative group. However, a greater gap may result from more

jobs rather than poor transit service. To that end a ratio of the access available to the two representative groups is proposed. Equations for each of these measures can be found in Table 3.1 under the heading *Relative Need*.

An alternative relative need based distributive justice concept involves the combination of the tax-based concepts of horizontal equity and vertical equity.[11] Horizontal equity states that individuals of equal standing should be taxed equally, and receive equal benefits associated with those taxes. Vertical equity states that disadvantaged groups should pay lower taxes than advantaged groups and furthermore that benefits associated with taxes should be distributed in such a way as to provide greater benefit to disadvantaged groups.

[11] (Grand 1984).

The concepts of horizontal and vertical equity are frequently used to evaluate transport systems. Delbosc and Currie use the concepts of horizontal and vertical equity in their 2011 assessment of public transport distributive justice.[12] They evaluate the distributive justice of the public transport system in Melbourne using Lorenz curves and the Gini coefficient. As applied in this chapter, the Gini coefficient is negative if lower income groups have relatively high levels of access to jobs in comparison to higher income groups, positive if the higher income groups have relatively higher levels of access, and zero if the groups have the same levels of access. The equation for the calculation of the Gini coefficient is shown in Table 3.1 under the heading *Relative Need*.

[12] (Delbosc and Currie 2011).

Minimum Allocation: Absolute Need		
Difference in Access to Jobs and Access to Workers at Location (i) within Threshold (t)	$A_{j-w} = a_{jobs,it} - a_{workers,it}$	(3.1)
Opportunity Level at Location (i) within Threshold (t)	$o_{it} = \frac{a_{jobs,it}}{a_{workers,it}}$	(3.2)
Equality of Opportunity		
Compare Person-Weighted Opportunity Level within Threshold t Experienced by various Representative Groups	$O_t = (\sum_i o_{it} S_i)/(\sum_i S_i)$	(3.3)
Maximin Theory of Justice		
Minimum PWA within Threshold (t) Experienced by a Representative Group	$Min \quad A_t = (\sum_i a_{it} S_i)/(\sum_i S_i)$	(3.4)
Minimum Person-Weighted and Time-Weighted Access Experienced by a Representative Group	$Min \quad A = \sum_i (A_t - A_{(t-y)}) e^{\theta t}$	(3.5)

Relative Need	
Gini Coefficient	$$G \approx 1 - \sum_{k=1}^{K} (p_k - p_{k-1})(a_k + a_{k-1}) \quad (3.6)$$
Net Auto PWA within Threshold t	$$A_{netauto,t} = A_{auto,t} - A_{transit,t} \quad (3.7)$$
Net Transit PWA within Threshold t	$$A_{nettransit,t} = A_{transit,t} - A_{walk,t} \quad (3.8)$$
Gap in PWA within Threshold t between People who Have an Automobile and People who Don't Have an Automobile	$$A_{hasauto,t} = (\sum_i a_{auto,it} S_{hasauto,i}) / (\sum_i S_{hasauto,i})$$ $$A_{noauto,t} = (\sum_i a_{transit,it} S_{noauto,i}) / (\sum_i S_{noauto,i})$$ $$A_{needgap,t} = A_{hasauto,t} - A_{noauto,t} \quad (3.9)$$
Ratio of Transit PWA within Threshold t to Auto PWA within Threshold t	$$A_{netauto,t} = \frac{A_{transit,t}}{A_{auto,t}} \quad (3.10)$$
Ratio of PWA within Threshold t of People who Don't Have an Automobile to PWA within Threshold t of People who Have an Automobile	$$Z_{needratio,t} = A_{noauto,t} / A_{hasauto,t} \quad (3.11)$$

Table 3.1: Operationalized distributive justice concepts

Description of the 48 US metropolitan areas

The 48 United States Metropolitan Areas evaluated in this chapter are the top largest 50 Core Based Statistical Areas (CBSA) by population, excluding Memphis and Kansas City due to issues with data collection. Table 3.2 provides information regarding the population, population densities, and mean travel time to work for each of the metropolitan areas and is arranged from largest population to smallest.

As can be seen the New York City Metropolitan Area has the largest population, weighted population densities, and mean travel time to work. In fact, the population and weighted population density in the New York City Metropolitan Area far exceed the next largest metropolitan area in either category. As a result it is anticipated that the New York City Metropolitan Area may generally be an outlier. The Riverside Metropolitan Area has the largest land area by far and may also be an outlier. In contrast, the Salt Lake City Metropolitan Area has the smallest population and overall population density. The Birmingham Metropolitan Area has the smallest weighted population density. Finally, the Buffalo Metropolitan Area has the lowest mean travel time to work. In general, these lowest values do not appear to be outliers.

Another characteristic is the number of jobs and workers, stratified by income in each metropolitan area. Note, that the breakdown of workers/jobs into the three categories of high, middle, and low income is not even. As defined by the US Census Bureau the low income bracket applies to incomes less than or equal to $1,250/month, the middle income bracket applies to incomes from $1,251/month to $3,333/month, and the high income bracket applies to incomes greater than $3,333/month. These definitions were originally developed to divide workers/jobs into three even groups, but several years have passed since that time and inflation has caused the relative percentage of workers/jobs in each group to shift.

The actual portions in each metropolitan area vary, but the high income brackets for workers and jobs generally include approximately 50% of the workers and jobs respectively, the middle income brackets for workers and jobs generally include slightly more than 25% of the workers and jobs respectively, and the low income brackets for workers and jobs generally include slightly less than 25% of the workers and jobs respectively. As a result, direct

comparison between these categories is inadvisable due to inevitable bias towards more jobs and workers as income levels increase. For this reason, the majority of the analysis will focus on access to all jobs, by a typical member of various representative worker groups.

Findings

Prior to this analysis, access to jobs and workers, broken down by income, was calculated for every census block in each of the 48 metropolitan areas, via four modes: automobile, transit, bicycle, and walking. This data was provided for use in this chapter by the Accessibility Observatory at the University of Minnesota. Data was available for six time thresholds: 10, 20, 30, 40, 50, and 60 minutes. However, see Table 3.2, only the threshold closest to the average mean travel time to work for all 48 metropolitan areas, which is the 30 minute threshold, is used in this analysis.

Absolute need

As noted in the theory section, it can be difficult to determine what minimal resources individuals are entitled too, especially in areas where general abundance inflates the social understanding of what a meaningful life within society entails. Transport is one of those areas. So rather than selecting a single minimum basic requirement for transport and evaluating if anyone falls below it, ratio of access to jobs over access to workers is spatially evaluated.

As can be seen in Figure 3.1, maps of opportunity level at a location and threshold allow for easy visualization of the opportunity to competition ratio, where opportunity is access to jobs and competition is access to workers, available to workers throughout a region. The ability to visualize these disparities is valuable in locating problem areas, such as the aforementioned bedroom communities, within a region. This technique can be especially valuable in determining where there may be issues with spatial mismatch of jobs and workers by industry, education level, or income level by simply looking at subsets of job opportunities and competing workers based on the specific type of job and worker of interest.

This is particularly useful in scenario comparisons for projects and before and after type analysis.[13] However, the measure discussed

[13] See chapter 18 and chapter 19.

Metro Area	2010 Population [people]	Overall Pop. Density [people/km^2]	Weighted Pop. Density [people/km^2]	Mean Travel Time to Work [minutes]
New York	18,897,109	1092	12071	36.30
Los Angeles	12,828,837	1022	4679	30.00
Chicago	9,461,105	508	3327	31.80
Dallas	6,371,773	276	1510	28.10
Philadelphia	5,965,343	501	3003	29.60
Houston	5,946,800	260	1587	30.20
Washington DC	5,582,170	385	2468	34.40
Miami	5,564,635	423	2857	29.10
Atlanta	5,268,860	244	839	31.30
Boston	4,552,402	504	3082	31.40
San Francisco	4,335,391	678	4691	33.20
Detroit	4,296,250	427	1468	26.60
Riverside	4,224,851	60	1661	31.90
Phoenix	4,192,887	111	1698	26.20
Seattle	3,439,809	226	1824	30.20
Minneapolis	3,279,833	210	1307	25.40
San Diego	3,095,313	284	2673	26.10
St. Louis	2,812,896	126	1059	25.60
Tampa	2,783,243	428	1284	27.00
Baltimore	2,710,489	402	2100	30.60
Denver	2,543,482	118	1856	27.70
Pittsburgh	2,356,285	172	1155	26.60
Portland	2,226,009	129	1689	26.60
Sacramento	2,149,127	163	1753	26.90
San Antonio	2,142,508	113	1342	26.40
Orlando	2,134,411	237	1072	27.90
Cincinnati	2,130,151	187	990	24.90
Cleveland	2,077,240	402	1471	24.70
Las Vegas	1,951,269	96	2521	25.00
San Jose	1,836,911	265	3252	28.10
Columbus	1,836,536	179	1231	23.60
Charlotte	1,758,038	220	727	26.90
Indianapolis	1,756,241	176	883	24.90
Austin	1,716,289	157	1210	26.50
Virginia Beach	1,671,683	246	1578	24.80
Providence	1,600,852	390	1840	26.20
Nashville	1,589,934	108	655	27.40
Milwaukee	1,555,908	413	2031	23.10
Jacksonville	1,345,596	162	834	26.20
Louisville	1,283,566	121	957	24.10
Richmond	1,258,251	85	840	24.50
Oklahoma City	1,252,987	88	992	22.50
Hartford	1,212,381	309	1256	23.90
New Orleans	1,167,764	152	1688	25.90
Buffalo	1,135,509	280	1595	22.00
Raleigh	1,130,490	206	715	25.90
Birmingham	1,128,047	83	508	26.20
Salt Lake City	1,124,197	45	1763	22.30
Average	3389201	281	1950	27.72

Table 3.2: Characteristics of the metropolitan areas evaluated in this chapter

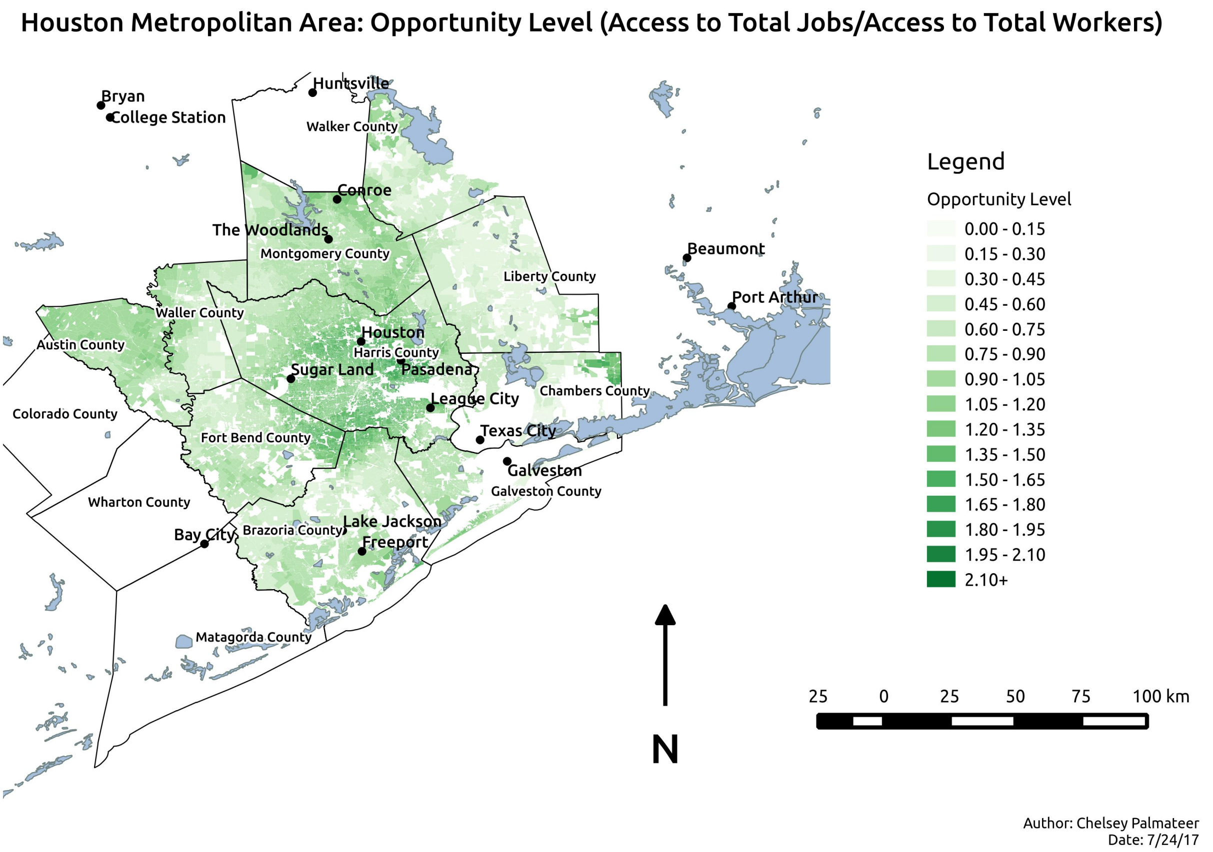


Figure 3.1: Houston metropolitan area: Opportunity level provided within 30 minutes

is unable to provide aggregate information on the community as a whole, and is therefore a poor choice for comparing between regions.

Equality of opportunity

As noted in the theory section, equality of opportunity requires that individuals all have an opportunity to reach a goal or desired outcome, such as accessing a job, without needing to overcome unrelated obstacles. In this chapter the goal is access to sufficient jobs to obtain a single job, and one potential unrelated obstacle might be high travel times reducing access for low income workers. In order to evaluate this, a person-weighted measure, which builds on the measure discussed in the previous section is utilized, see Equation 3.3. Basically, the goal is to compare the opportunity level, or person-weighted ratio of access to jobs over access to workers

Workers by Income Category	Jobs by Income Category Low	Middle	High	All
Low	1.0707	1.0719	1.1115	1.1048
Middle	1.0698	1.0703	1.1075	1.1150
High	1.0784	1.0744	1.1158	1.0748

Table 3.3: Person-weighted opportunity level (job access/worker access) via auto for workers and jobs by income category for Houston

within 30 minutes, as experienced by each income group. However, there are several ways to approach this task.

To help clarify the potential opportunity level definitions, consider Table 3.3. This table has three rows of data, one row for each of the income brackets that the opportunity levels were person-weighted by. In addition, there are four columns of data. The first column relays the person-weighted ratio of access to low income jobs over access to low income workers. The second column does the same but for middle income jobs and workers rather than low income. The third column relays the person-weighted ratio of access to high income jobs over access to high income workers. The final column, relays the person-weighted ratio of access to all jobs over access to all workers. Ideally, an analysis regarding a person's opportunity to find a job would focus on jobs within that person's income bracket, or presumed skill level. However, due to the uneven distribution of the income brackets noted previously this leads to some bias. In particular note that in general, regardless of the income bracket that the opportunity level has been person-weighted over, the person-weighted high income opportunity level is greater than the person-weighted middle income opportunity level, which is greater than the person-weighted low income opportunity level.

To avoid this bias, rather than comparing opportunity levels stratified by income for different income groups, all comparisons will be made between person-weighting of differing income levels on the all incomes opportunity level.

Figure 3.2 relays the person-weighted ratio of access to all jobs over access to all workers for each income group in each metropolitan area via two modes: auto and transit. Each point in the graph represents a metropolitan area and is labeled by an airport code in use within that metropolitan area. Income groups are color coded. In addition there is a dashed line on the 45 degree diagonal of the chart. At first glance, regardless of the person-weighting income level, the measures seem to be around 1, but this isn't quite the case. Access to jobs (which tends to be more

concentrated) is generally higher than access to workers (who tend to be more dispersed), especially by transit. In order to determine if the person-weighted opportunity levels for the various income levels and modes can be considered statistically equal, several homoscedastic Student's t-tests are performed. These tests check the null hypothesis that the distributions of person-weighted opportunity levels for the various income levels in the 48 metropolitan areas is essentially the same. They also assume that all of the samples have the same underlying variance, based on the analysis this assumption is believable, with estimated variances ranging from 0.0060 to 0.0085. There is one exception, the high income person-weighting for transit actually has an estimated variance of 0.0217.

Interestingly the tests indicate that high income workers have statistically different opportunity levels via transit than workers with other income levels via transit, but that the high income workers have statistically similar opportunity levels between the two modes. Tests also indicate that middle income workers have statistically different opportunity levels between the two modes. However for opportunity levels via auto, there does not appear to be a statistical difference between the opportunity levels experienced by the various income groups. Together these findings show that automobiles provide equality of opportunity between income groups, assuming that everyone has access to an automobile, whereas transit does not provide equality of opportunity between income groups.

Maximin theory of justice

Although the maximin theory of justice relies on equality of opportunity in regards to obtaining positions of responsibility within a society, the theory does not require an equal opportunity in regards to the distribution of benefits to all representative groups. Instead this theory is derived under the assumption that justice is achieved when working within a society raises the expected benefits of every member of that society, and maximizes the benefit experienced by the representative group of individuals who experience the least benefit. To that end Equation 3.4 is used to determine the person-weighted access to jobs for each income level group of workers in each metropolitan area. Then the person-weighted access (PWA) of the group with the least access is

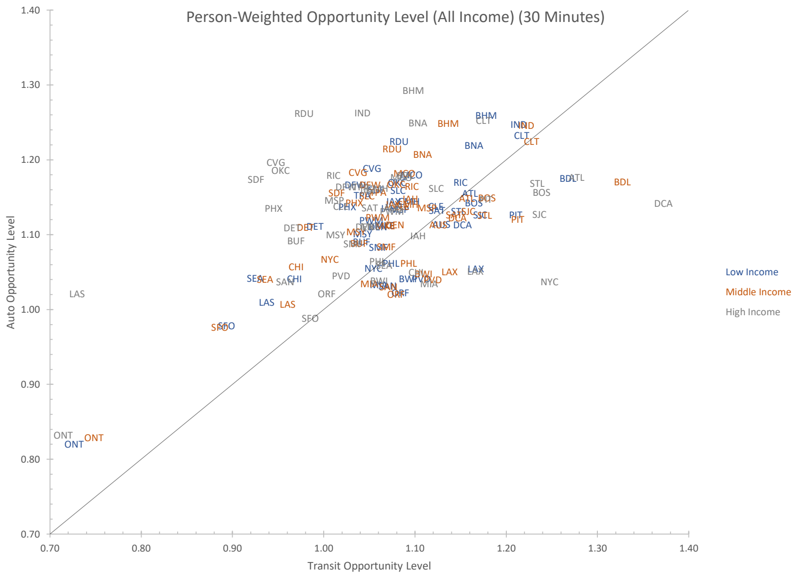


Figure 3.2: Person-weighted opportunity level (access to jobs / access to workers) provided within 30 minutes

selected as the observed lowest access for a representative group in each metropolitan area. The results can be seen in Table 3.4.

A naive analysis might apply the maximin procedure indicated in the maximin theory at this point and declare that Los Angeles has the most just distribution of access via auto, and New York has the most just distribution of access to jobs via transit within 30 minutes as well as the most just distribution of transport services within 30 minutes. However Table 3.4 shows that there is a clear (and it turns out statistically significant) correlation between the maximin access variables via transit and weighted population density. So when determining the justice of each of these regions by the maximin definition it is best to control for factors outside the characteristics of the transport network, using a regression model.

Figure 3.3 is a graphical representation of such a comparison. Points on this line indicate that the actual observed measure equals the prediction, points above the line indicate that the actual observed measure exceeds the prediction and points below the line indicate that the actual observed measure is less than the prediction. Since the maximin theory indicates that situations are more just when the group with the least benefit is higher, metropolitan areas in which the point is at or above the line are considered just, while those below are considered unjust.

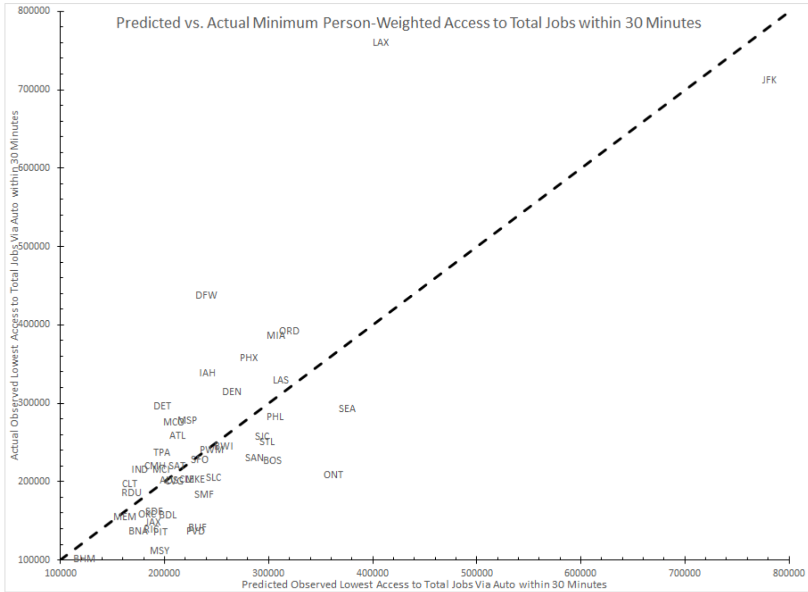


Figure 3.3: Predicted vs. actual maxi-min theory of justice applied to access to all jobs via auto within 30 minutes

The limitation of this particular measure is that it is unable to take into account a potential desire to mitigate issues with distributions of other benefits in society. So for example, it may be desirable, to supplement the transport services provided to low income individuals. Rawls' system is of limited use in evaluating the potential use of transport distribution favoring certain representative groups to mitigate other obstacles faced by those groups. To understand this, consider Table 3.4 again. There are columns in the chart indicating which representative group is the group with the least benefit. Often, for both transit and auto, the representative group experiencing the lowest level of access within 30 minutes for a given region is either the high or middle income group of workers. This makes it difficult to determine what benefit the low income group receives and what difficulties they might be experiencing.

Relative need

When questions of distributing benefits to mitigate for other factors are considered, the focus is on measures which can accommodate an understanding of the relative need, due to circumstances external to the distribution of goods and services being considered, of representative groups. As noted in the discussion, the concepts of

Metro Area	Observed Lowest Access Via Auto	Income Category	Observed Lowest Access Via Transit	Income Category
New York	711,779	High	40,520	Middle
Los Angeles	760,551	High	10,994	High
Chicago	392,353	Low	11,134	Low
Dallas	437,544	High	3,009	Low
Philadelphia	283,037	High	8,192	High
Houston	338,829	High	3,584	Low
Washington DC	270,748	Low	7,574	Low
Miami	386,699	High	5,121	High
Atlanta	258,631	Middle	1,841	Middle
Boston	226,736	Low	8,757	Low
San Francisco	292,410	Low	16,578	Middle
Detroit	296,636	High	1,713	High
Riverside	209,151	Low	1,443	High
Phoenix	358,230	High	2,932	High
Seattle	204,625	Low	5,943	Low
Minneapolis	277,720	High	3,799	High
San Diego	257,841	Middle	3,867	High
St. Louis	220,345	High	2,366	High
Tampa	236,745	Low	2,349	High
Baltimore	245,149	High	4,667	High
Denver	314,731	High	5,623	High
Pittsburgh	135,398	Middle	3,898	High
Portland	239,964	Low	6,381	High
Sacramento	183,465	High	2,461	High
San Antonio	228,188	High	2,834	High
Orlando	275,395	High	1,774	Middle
Cincinnati	200,334	Middle	1,636	High
Cleveland	203,384	High	2,429	High
Las Vegas	328,906	High	2,344	High
San Jose	251,131	Low	4,357	Low
Columbus	220,178	Middle	2,725	High
Charlotte	197,264	Middle	1,780	Middle
Indianapolis	215,977	High	1,887	High
Austin	201,880	Low	3,426	High
Virginia Beach	138,608	High	1,422	High
Providence	136,533	High	2,372	High
Nashville	137,261	Middle	1,751	High
Milwaukee	202,925	High	4,371	High
Jacksonville	148,448	High	1,402	High
Louisville	161,724	Middle	2,026	High
Richmond	139,070	Middle	1,951	High
Oklahoma City	157,877	High	1,559	High
Hartford	157,086	High	1,649	High
New Orleans	111,327	High	3,120	High
Buffalo	141,115	High	2,420	High
Raleigh	186,227	Middle	1,420	High
Birmingham	101,850	Middle	756	High
Salt Lake City	229,745	Low	4,526	High

Table 3.4: Maximin theory of justice applied to access to all jobs within 30 minutes

horizontal equity and vertical equity provide the focus on, and understanding of, how some goods, such as transport services, are distributed similarly between some groups, such as groups defined by race, but differently between other groups, such as groups defined by income or purchasing ability. The focus here is on the distribution of transport services as it relates to income disparities and the ability to own and maintain an automobile.

There are many potential ways to measure the relative amount of services provided to income groups and as well as the relative amount of services provided to those with and without access to certain modes. To begin assume that everyone can access all modes. In such a case only the relative amount of services provided by income group is relevant. The Gini coefficient (Equation 3.6), and Lorenz curves provide an excellent and well used means to evaluate the relative transport service, especially in terms of access to jobs, provided to different income groups.

At this point it is noted that generally, when the focus is to evaluate the level of equal service between groups, the groups would be organized in increasing order by the amount of the good/service provided. This would result in only positive or zero values of the Gini coefficient, with zero being considered equitable or just. However in this case, to allow for comparison between groups and consistency in analysis for each metropolitan area, the groups were organized in increasing order by income. For this reason, the Gini coefficient can have positive, negative, and zero value.

In this case many of the metropolitan areas have negative Gini coefficients. This indicates that low and/or middle income groups have higher levels of access via the given mode than the high income group. If the Gini coefficient was zero it would indicate that the groups have the same access levels. Finally, positive values of the Gini coefficient indicate that the high and/or middle income groups have higher levels of access than the low income group.

As noted previously, for both modes, the majority of metropolitan areas have negative Gini coefficients. This indicates that in general lower income individuals are geographically located in areas with higher levels of access. This is corroborated by many studies of spatial characteristics of urban areas in the United States.

Unfortunately looking at only the resulting Gini coefficient does not provide much more information than that. However if the Lorenz curve is constructed for the region and compared to the Lorenz curve

of a situation with perfectly equal levels of access, it would be further possible to determine which specific groups have higher levels of access and which have lower levels of access, within a given mode.

Furthermore, the initial assumption that all individuals have access to all modes is flawed. There are costs associated with automobile ownership or rental, as well as costs associated with using transit. For some individuals these costs are a hardship, and for others they are simply not affordable, leaving some individuals without or with only limited access to these transport modes.

Figure 3.4 shows the additional level of access experienced by the typical user who can afford to take transit rather than walk, or use an automobile rather than take transit in each of the metropolitan areas. Notice that the scale for the value added by transit is significantly lower than that for automobile use. In fact the most value added in any of the metropolitan areas by transit is less than half of the least value added in any of the metropolitan areas by automobile. For this reason it may be worthwhile to consider subsidizing automobile ownership in areas without the density to support transit.

An alternative is to use ratios of two types of access. That is the case for the measures shown in Table 3.5, which are calculated using Equation 3.9 and Equation 3.10.

Incorporating the information about which individuals do and do not have an automobile makes a very large difference when using ratios. In fact for most metropolitan areas, the needs ratio, which presents the ratio of transit access for the typical user who does not have an automobile to auto access for the typical user who does have an automobile, is nearly double or more than double the ratio of transit access for a typical user to the auto access for a typical user. This indicates that individuals who do not have a car, whether by choice or necessity tend to select housing near transit services and that transit services tend to be focused in areas with demand. However, the need ratio is still quite small. This reiterates the conclusion that it is worthwhile to consider subsidizing automobile ownership in areas without the density to support transit.

Table 3.5: Evaluating distributive justice based on ratios of access by mode

Metro Area	Ratio of Transit Access to Auto Access Low Income	Middle Income	High Income	Needs Ratio
New York	0.0659	0.0573	0.0968	0.2144
Los Angeles	0.0183	0.0175	0.0157	0.0319
Chicago	0.0302	0.0320	0.0497	0.1004
Dallas	0.0071	0.0072	0.0075	0.0127
Philadelphia	0.0360	0.0390	0.0309	0.1126
Houston	0.0099	0.0098	0.0124	0.0204
Washington DC	0.0154	0.0151	0.0213	0.1086
Miami	0.0147	0.0147	0.0144	0.0251
Atlanta	0.0078	0.0076	0.0096	0.0220
Boston	0.0432	0.0457	0.0480	0.1251
San Francisco	0.0609	0.0598	0.0647	0.1797
Detroit	0.0065	0.0064	0.0056	0.0125
Riverside	0.0076	0.0077	0.0066	0.0103
Phoenix	0.0093	0.0095	0.0082	0.0204
Seattle	0.0328	0.0342	0.0375	0.0964
Minneapolis	0.0068	0.0070	0.0059	0.0432
San Diego	0.0153	0.0159	0.0139	0.0314
St. Louis	0.0058	0.0058	0.0050	0.0266
Tampa	0.0111	0.0110	0.0101	0.0203
Baltimore	0.0242	0.0261	0.0187	0.0713
Denver	0.0185	0.0188	0.0190	0.0453
Pittsburgh	0.0317	0.0325	0.0290	0.0744
Portland	0.0103	0.0107	0.0090	0.0646
Sacramento	0.0158	0.0164	0.0150	0.0356
San Antonio	0.0172	0.0172	0.0126	0.0349
Orlando	0.0067	0.0066	0.0070	0.0124
Cincinnati	0.0111	0.0106	0.0084	0.0285
Cleveland	0.0160	0.0155	0.0122	0.0360
Las Vegas	0.0109	0.0111	0.0073	0.0221
San Jose	0.0157	0.0161	0.0157	0.0251
Columbus	0.0166	0.0160	0.0136	0.0329
Charlotte	0.0106	0.0103	0.0119	0.0204
Indianapolis	0.0123	0.0120	0.0092	0.0281
Austin	0.0191	0.0186	0.0169	0.0400
Virginia Beach	0.0125	0.0122	0.0103	0.0221
Providence	0.0112	0.0123	0.0081	0.0442
Nashville	0.0143	0.0130	0.0129	0.0422
Milwaukee	0.0296	0.0301	0.0220	0.0525
Jacksonville	0.0120	0.0114	0.0097	0.0266
Louisville	0.0183	0.0167	0.0127	0.0445
Richmond	0.0181	0.0170	0.0144	0.0425
Oklahoma City	0.0125	0.0125	0.0100	0.0214
Hartford	0.0205	0.0232	0.0120	0.0456
New Orleans	0.0301	0.0286	0.0278	0.0634
Buffalo	0.0222	0.0229	0.0171	0.0437
Raleigh	0.0090	0.0087	0.0071	0.0216
Birmingham	0.0098	0.0095	0.0072	0.0233
Salt Lake City	0.0223	0.0226	0.0202	0.0468

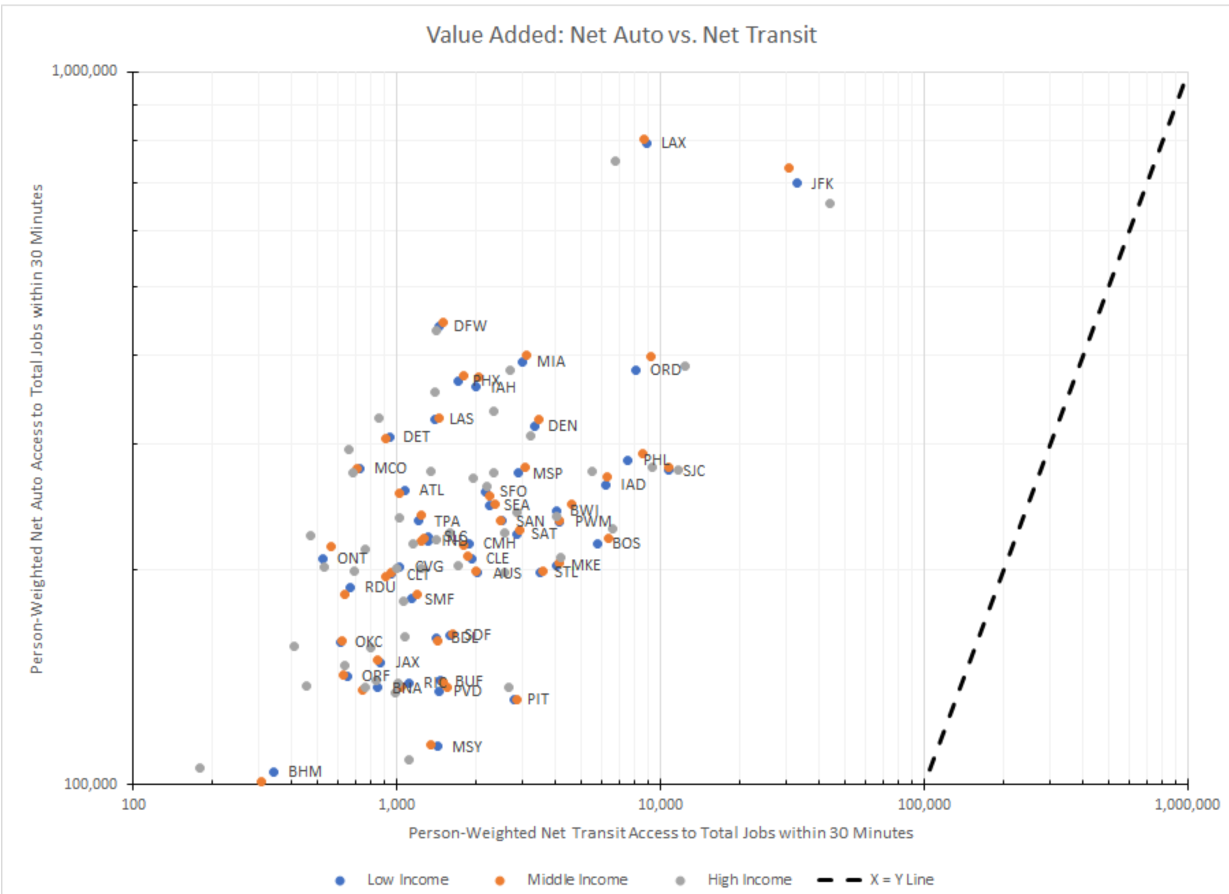


Figure 3.4: Net auto vs. net transit access to all jobs via auto within 30 minutes

Conclusions

Each of the measures of distributive justice in transport explored here provide valuable information regarding the justice of a regional transport system. It is also apparent that these measures have differing strengths and weaknesses.[14]

[14] This is further elaborated on the Dissertation on which this is based: (Palmateer 2018).

The absolute minimum allocation measure is excellent for local analysis particularly determining the location of problem areas in relation to job worker balance and generally gauging the level of competition experience by system users and overall shape of the distribution of transport services. The equality of opportunity analysis provides a basis for direct statistical comparison of transport services between groups that can be scaled to a variety of geographic areas. The maximin theory works well for comparing between regions, once region size is controlled for, but does poorly at comparison between groups. Relative need measures on the other hand provide many opportunities to compare between groups both within a single mode and between modes, and can also be scaled within or between regions, though only between region analysis is shown here.

Next

This research could provide a foundation for the following suggested future work:

- To verify the findings relating land use and network characteristics to distributive justice it is necessary to perform a cross-sectional time series analysis rather than a cross-sectional analysis of a single point in time. This will require additional data that is not yet available.
- To test the importance of distributive justice as an objective in transport planning it is recommended that a network growth model be developed that can accommodate user selected objective functions. The model should then be run for at least three scenarios: minimization of system travel time, maximization of access, and maximization of distributive justice, based on one or more of the distributive justice measures developed in this dissertation.
- To test the importance of distributive justice in economics, it would be valuable to run a times series cross-sectional analysis of

unemployment based on residential distributive justice measures and other variables.

- This research focused on the automobile and transit modes. Future work could address justice issues in additional modes including the impacts of Americans with Disabilities Act non-compliant facilities on the ability of individuals to utilize the pedestrian network or the potential advantages of supplementing low income households transport options with ride-share vouchers.

- It could be of interest to evaluate the impacts of a land development project, or disentangle the impacts of a joint transport/land development project such as a transit oriented development project, utilizing the distributive justice measures.

4
Disparity of Access: Variations in Transit Service by Race, Ethnicity, Income, and Auto Availability

Elisa Borowski, Alireza Ermagun, and David Levinson

Abstract: This chapter explores the relationship between transit access to jobs and minority races, low- and middle-income households, and carless households at the block group level for the 50 largest metropolitan regions by population in the United States. A log-linear regression model is used to identify inequalities in transit access to jobs using data collected from the American Community Survey, the Environmental Protection Agency's Smart Location Database, and the Access Across America database. The intra-metropolitan analyses reveal that access is unevenly distributed across block groups that have different densities of race and levels of income. The differences in access are especially apparent where there are denser pockets with higher percentages of African Americans, Hispanics, low-income households, and carless households. The inter-metropolitan analyses show that access is unevenly distributed across metropolitan regions when considering various socio-demographic populations. Different metropolitan regions provide different levels of access for all investigated socio-demographic categories, whether considering racial minorities, levels of income, or car ownership. The results may inform recommendations for equitable transport planning and policy-making.

Introduction

Keywords: Access; Equality; Environmental justice; Public transit; Urban planning; Urban form

Title VI of the US Civil Rights Act of 1964 requires that no federally funded program or activity discriminates against any individual on

the basis of race, color, or national origin.[1] Access is the ease with which an individual may "use, enjoy and participate in the many aspects of society, including work, commerce and leisure activities."[2] Although well-designed public transit systems should enable individuals to achieve desired activities given their choice of location, time of day, and day of the week, transit agencies are far from this ideal figure.[3] According to the Brookings Metropolitan Policy Program Opportunity Series, a typical job in the US is accessible by public transit within 90 minutes or less by only 27% of the surrounding workforce when considering the 100 largest metropolitan areas in the nation.[4]

Over the past two decades, research has acknowledged the importance of equitable access and its need for improvement in many locations.[5] Researchers have selected different geographical scale ranging from Transport Analysis Zone (TAZ)[6] to census block level[7] in access and equity analysis. Not surprisingly, previous studies have leaned toward access to jobs by transit among all available modes of travel and valued destinations.

The results reported in more qualitative studies display a variety of trends. Those studies reporting a positive relationship between access and low-income groups often discuss the prevalence of low-income neighborhoods surrounding public transit stations in that area of study.[8] When a single study reports both positive and negative trends between access and low-income populations, it often depends on the trip purpose or the type of job accessible.[9] Insignificant results indicate no difference in access between low-income households and middle- or high-income households.[10] Most qualitative studies report a negative relationship between carless households and access.[11] However, most of these studies include both transit access and auto access, and the results indicate that transit-dependent individuals have lower access compared to car-owning households. Single studies showing both positive and negative relationships for access of carless households often indicate that it is contingent upon the applied time threshold.[12] Finally, the results of the qualitative studies depict no clear trend between access and African American population share. While negative relationships are often explained by the absence of proximal opportunities, mixed results indicate that the sign of the relationship is contingent upon the trip purpose or whether the household owns a car.

[1] (US Census Bureau 2019).

[2] (US Department of Transportation 2019).

[3] See chapter 14 in this volume.

[4] (Tomer 2012).

[5] (Ermagun and Tilahun 2020).

[6] (Shen 1998).

[7] (Farber et al. 2014).

[8] (Farber and Marino 2017, Foth et al. 2013).

[9] (Chen and Akar 2017, Grengs 2015).

[10] (Blumenberg and Shiki 2003, Hu 2015).

[11] (Blumenberg and Shiki 2003, Grengs 2010, Shen 1998, Tilahun and Fan 2014).

[12] (Farber and Marino 2017).

This chapter builds on the valuable contributions of the location-specific studies summarized herein to provide a clearer description of access equality across the nation. This work extends the research efforts of earlier studies by examining a comprehensive national data set, using disaggregate data analysis at the block group level, including built environment variables like road network density, and providing equality comparisons both between and within the 50 largest metropolitan regions in the US.

Questions

This chapter explores access equity in terms of race, income, and vehicle ownership for the 50 largest metropolitan regions in the US using data aggregated at the block group level while testing linear regression models. Our contribution to the current body of literature is twofold. First, we explore the transit access to jobs and minority races, low- and middle-income households, and carless households at the block group level for the 50 most populous metropolitan regions in the US. We present an analysis that looks at multiple metropolitan regions as opposed to one selected city or metropolitan region. Second, we compare the level of access provided to different socio-demographic groups between and within regions. The intra-metropolitan area analysis provides a clearer understanding of equity of access. The inter-metropolitan area analysis, however, helps rank metropolitan regions across the US by transit-based job access provided to disadvantaged socio-demographic populations. In particular, this chapter addresses the following questions:

- Is access by transit positively correlated with carless households?
- Is access negatively correlated with low-income households or minority dense population?
- Is access unevenly distributed within and between metropolitan areas?
- Is access positively correlated with road network density?

We develop a set of logarithmic regression models at the block group level for the 50 largest metropolitan areas in the US using three data sources: (1) American Community Survey, (2) Access Across America, and (3) Smart Location Database. We employ

regression models to explore how access levels vary with different socio-demographic variables. We do not make claims of causality; however, we state that access is a function of policy which has a social and spatial dimension. When we see a mismatch between needs and access, it suggests a lack of policy emphasis on targeting specific locations with needs. What the regression model clarifies is how access shifts with socio-demographic variables, and it offers an easy way of demonstrating to what extent changes in access are "responsive" to changes in variables of socio-demographic. This chapter provides a reference for researchers, city officials, and transit agencies in large metropolitan areas across the US to assist in improved allocation of resources, prioritization of transport projects, and guided policy-making to achieve the Title VI requirement of equitable access services for all individuals.

Methods

Data

The data used for the analysis in this chapter are extracted from (1) American Community Survey, (2) Access Across America, and (3) Smart Location Database.

American Community Survey. The American Community Survey is an ongoing survey conducted by the US Census Bureau wherein most participating households receive a short version of a questionnaire, while one in six households receive a long-form each year.[13] For this research, the five-year span American Community Survey from 2011 to 2015 provided socioeconomic variables at the block group level for the 50 largest by population metropolitan regions in the US. The extracted socioeconomic data on race and income allowed for the testing of the hypothesis that job access by transit is unevenly distributed among various demographic groups. The data were downloaded from the electronic archives and augmented with the following two additional data sets.

[13] (US Census Bureau 2019).

Access Across America. This is a data set organized by the Accessibility Observatory at the University of Minnesota which began in 2013. The data used in this study are from 2015 and include the number of jobs accessible by transit within time thresholds of 10, 20, 30, 40, 50, and 60 minutes for the 50 largest

metropolitan regions in the US.[14] The transit travel times were captured during the period of 7:00 AM to 9:00 PM considering departures at one-minute intervals, and they include access and egress segments, as well as transfers. This block level data set provides a locational access measure. To calculate a worker-weighted access measure, Owen and Murphy recommended weighting the locational access measure by the number of workers residing in each block and then averaging these values across the metropolitan region.[15] The weighted access ranking could then be found by averaging the worker-weighted access values across the various time thresholds for each metropolitan region. These data were extracted from the database and then aggregated at the block group level for use with the American Community Survey data. This analysis applied a 30-minute time threshold, because it is closest to the reported average mean travel time to work across the metropolitan regions of interest.

[14] (Owen and Murphy 2020).

[15] (Owen and Murphy 2020).

SMART LOCATION DATABASE. The Smart Location Database was started by the US Environmental Protection Agency as part of the Smart Growth Program to offer free data for analysis of efficiency of place across the entire US through indicators such as density, diversity, design, destinations, and distance.[16] The data is collected from a variety of sources including multiple Census data sets, the Protected Areas Database of the United States, in addition to databases focusing on highways, streets, parks, and transit. This source provided research data from 2010 on land area, carless households, and road network density at the census block group level. This allowed for the testing of hypotheses related to the correlation between job access by transit and population density, carless households, and the physics of the network. The use of both socio-demographic and built environment variables in this study is a novel feature that improves the accuracy of the analysis by accounting for additional significant effects. All three data sets used in this study are rich with many observations, providing a fine level of detail throughout this investigation.

[16] (Ramsey and Bell 2014).

Variable description

The variables considered in this study for the development of the regression model are defined in Table 4.1. The greatest African American population density was observed in Cincinnati. The

Variable	Definition	Average	St. Dev.
Access	Transit access to jobs in 30 minutes at the block group	45,072.46	184,387.35
No AA	1: No African Americans are reported at the block group; 0: Otherwise	0.23	0.42
AA Density	African American population density at the block group (People/Acre^2)	16.93	3,114.70
No Hispanics	1: No Hispanics are reported at the block group; 0: Otherwise	0.12	0.32
Hispanic Density	Hispanic population density at the block group (People/Acre^2)	94.92	26,456.80
Non AA H Density	Non African American and Hispanic population density (People/Acre^2)	1,436.66	468,609.64
Low Income	Percentage of households earning less than $25,000 annually at the block group	21.42	16.57
Middle Income	Percentage of households earning $25,000 - $50,000 annually at the block group	21.74	11.61
Zero-Car	Percentage of carless households at the block group	11.15	16.63
Road Density	Road network density at the block group (mile/mile^2)	17.89	9.15

Table 4.1: Description of variables used in regression analysis

greatest Hispanic population density, non-African American, non-Hispanic population density, road network density, and number of jobs accessible by transit within 30 minutes were all found in New York. The smallest road network density was from a block group in Providence. The values identifying the income category cutoffs were determined through the development of the national level regression model wherein the earliest iterations of the model included income categorical ranges at their most disaggregate level identical to those provided by the American Community Survey. The results of the model informed the income category boundaries to ensure that the final ranges distinguishing between low-, middle-, and high-income accurately reflected the trends observed in the data in its most disaggregate form. Finally, the data were cleaned by removing observations consisting of zero land area, zero road network density, zero job access, zero household income, or zero non-African American, non-Hispanic individuals. This cleaning process removed a total of 2,638 observations, resulting in a remainder of 108,903 observations for use in the analysis.

Hypotheses and modeling

We test four distinct hypotheses:

- *H*1: Job access by transit is positively correlated with carless households. This may be due to the lifestyle choices of many individuals living in transit-oriented development areas.
- *H*2: Job access is negatively correlated with low-income households or minority dense populations. This may be due to the often expensive or exclusive access to property.
- *H*3: Access is unevenly distributed within and between metropolitan areas.
- *H*4: Job access is positively correlated with road network density. We believe this is due to the increased connectivity of the built environment.

A set of multivariate log-linear regression models were developed to estimate correlations between socioeconomic factors and transit access to jobs within a 30-minute threshold at the census block group level as a function of the socioeconomic characteristics of the block groups. First, the regression model was developed using the national data set. After finalizing the national level regression model, data from each metropolitan region were analyzed individually using the same regression model structure.

The coefficients are presented in Table 4.2 for the seven variables of interest for each of the 50 metropolitan models as well as the national model. A t-test score with an absolute magnitude of 1.96 or higher is required for the finding to be considered statistically significant in this study. The only two variables with statistically significant findings for all 50 metropolitan regions were Percent Zero Car Household and Road Network Density. They are also the only two variables with entirely positive coefficients, meaning that the relationship between transit access to jobs and carless households or road network density is unvaryingly positive regardless of the metropolitan area. The adjusted R^2 in the national model is 0.68. The lowest adjusted R^2 value is 0.37 from the Las Vegas model and the highest is 0.78 from the Milwaukee model. The number of observations at the national level was 108,903, and the number of observations ranged from 564 in Raleigh to 13,518 in New York, with an average of 2,178 observations per metropolitan region.

Findings

To examine the distribution of access among different socio-demographic groups, and the extent of uneven distribution, we calculate the elasticity of variables for each metropolitan area. Figure 4.1 visually depicts the relationship between transit access to jobs and the seven variables of interest with statistically significant results. The total number of metropolitan areas for each of the six plotted variables is not consistently 50, because some parameters were found to be insignificant in some metropolitan models, and therefore, those metropolitan areas could not be included in the ranking for that category. As shown in Figure 4.1a, the elasticities of African American Density are entirely positive, meaning the relationship between the number of African American individuals per acre of land and the number of jobs accessible by transit within 30 minutes is positive across the 50 largest metropolitan regions in the nation. Pittsburgh (with an elasticity of 0.20) and Hartford (0.15) stand out as providing the more equal access for African American dense areas. The subsequent decline in access is relatively steady and drops off quickly in Detroit (0.04) and Dallas (0.03).

Looking at Figure 4.1b, it is found that the elasticities of Hispanic Density for 96% of the studied metropolitan regions were positive and negative for 4% of the regions, meaning the relationship between the number of Hispanic individuals per acre of land and the number of jobs accessible by transit within 30 minutes is positive for the majority of the 50 largest metropolitan regions in the nation. Riverside provides the highest level of access for areas with a high share of Hispanic individuals, with an elasticity of 0.43. Richmond is the only metropolitan region with a statistically significant negative relationship (-0.11) between the number of Hispanic individuals per acre and job access by transit. As shown in Figure 4.1c, the elasticities of Non African American and Hispanic Density for 97% of the regions were positive and negative for 3% of the regions, meaning the relationship between the number of non-African American, non-Hispanic individuals per acre of land and the number of jobs accessible by transit is positive for the majority of the 50 largest metropolitan regions in the nation. San Francisco provides the highest level of transit access for areas dense in non-African American, non-Hispanic individuals, with an elasticity of 0.41. There is initially a steep decline in access across the top seven ranked metropolitan areas from San Francisco to

Boston. The decline in access then tapers off with Orlando as the only metropolitan area showing a negative relationship (-0.11) between job access and the number of non-African American, non-Hispanic individuals per acre.

For the variable Percent Low Income shown in Figure 4.1d, the elasticities for 87% of the metropolitan regions were positive and negative for 13%, meaning the relationship between the percentage of households earning less than $25,000 annually and the number of jobs accessible by transit is positive for the majority of the 50 largest metropolitan regions in the nation. Las Vegas stands out as providing the best level of access for low-income households, with an elasticity of 0.24. The elasticity of access at the national level is nearly zero, indicating that transit access is on average no better or worse for households earning less than $25,000 annually compared to other income groups across the nation. However, six metropolitan regions show a statistically significant negative relationship between transit access and low-income: Boston, Washington, Chicago, Pittsburgh, Memphis, and New York. New York ranked last with an elasticity of -0.14.

Considering the variable Percent Middle Income shown in Figure 4.1e, the elasticities for 77% of the metropolitan regions were positive and negative for 23%, meaning the relationship between the percentage of households earning between $25,000 and $50,000 annually and the number of jobs accessible by transit within 30 minutes is positive for the majority of the 50 largest metropolitan regions in the nation. However, it is important to note that the sign for this variable in the national model is negative, meaning overall in the US, middle-income households experience less job access by transit than other income groups. Las Vegas (elasticity of 0.30) by far provides the best transit access for households earning between $25,000 and $50,000 annually. In the national model, there is a negative correlation between job access and middle-income households, indicating that in general middle-income households have worse transit access compared to households of other income levels (elasticity of -0.02). A total of seven metropolitan areas show a statistically significant negative relationship between middle-income households and job access: Boston, Chicago, St. Louis, Washington, New York, New Orleans, and Pittsburgh. For the variable Percent Zero Car Household shown in Figure 4.1f, New York by far provides the best access to carless households, twice as well the second ranked region of Chicago. An additional six metropolitan

regions stand out above the rest in providing access to carless households: Washington, Boston, San Francisco, Philadelphia, Pittsburgh, and Buffalo. The subsequent decline in access is steady and mild. Providence ranks last with an elasticity of 0.05.

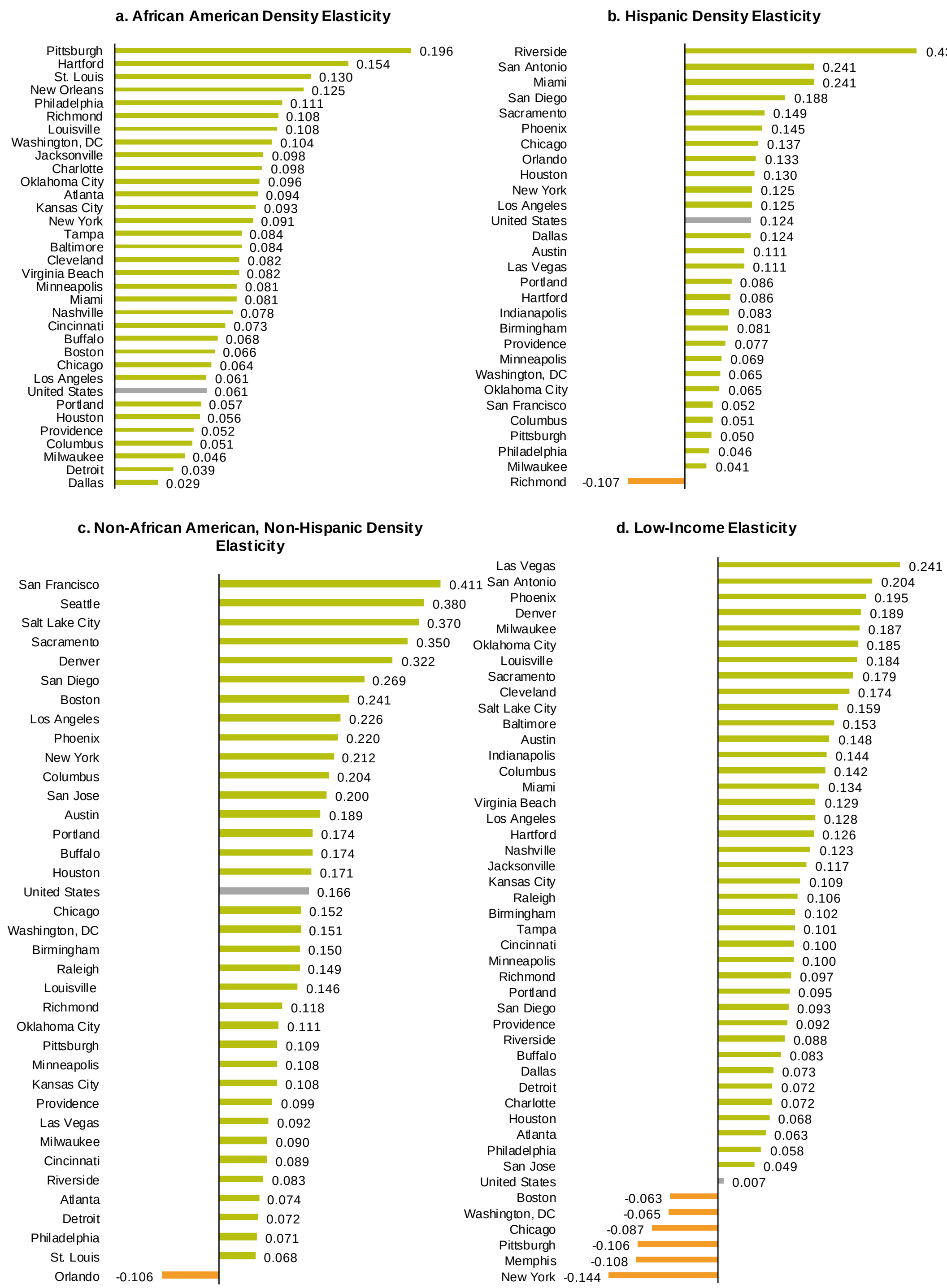
Our first hypothesis ($H1$) was a positive correlation between job access by transit and carless households. $H1$ was confirmed for 33 metropolitan regions, while the remaining regions were statistically insignificant. Our second hypothesis ($H2$) was a negative correlation between job access and minority race individuals or low-income households. $H2$ was only confirmed in one case for racial minorities (i.e., access provided to Hispanic individuals in Richmond) and in 6 out of 45 metropolitan regions for low-income households. Therefore, $H2$ was largely refuted.

Our third hypothesis ($H3$) was that access is unevenly distributed within and between metropolitan regions. As determined through intra-metropolitan analyses, access is unevenly distributed across block groups that have different densities of race and levels of income. The inter-metropolitan analyses show that access is unevenly distributed across metropolitan regions throughout the nation when considering any socio-demographic population. It should be noted that elasticities reported here describe percent change rather than providing a per person evaluation. For example, the access elasticity in Las Vegas is 0.240 for percent low-income households and 0.297 for percent middle-income households. However, a 1% increase in low-income households would equate an additional 1,562 low-income households, and a 1% increase in middle-income households would equate an additional 1,912 middle-income households. Therefore, at the household level, the change in job access for the two groups is approximately equal, although when considering elasticity as percentage change, change in access appears greater for the larger group. Different metropolitan regions provide different levels of access in all investigated socio-demographic categories, whether considering racial minorities, levels of income, or car ownership. For example, the best regions for providing access to African Americans, Hispanics, low-income households, and carless households are Pittsburgh, Riverside, Las Vegas, and New York, respectively. No metropolitan region ranks highly in providing to all disadvantaged socio-demographic groups investigated in this study, a result that has important implications for equity and transport justice.

Region	AA Density	Hispanic Density	Non AA H Density	Low Income	Middle Income	Zero Car	Road Density	Adj. R^2	Observations
Atlanta	0.09	-	0.07	0.002	-	0.018	2.32	0.62	2,536
Austin	-	0.11	0.18	0.007	0.006	0.023	1.53	0.69	960
Baltimore	0.08	-	-	0.008	0.004	0.007	2.07	0.75	1,849
Birmingham	-	0.08	0.15	0.003	-	0.013	1.80	0.70	761
Boston	0.06	-	0.24	-0.003	-0.002	0.017	1.64	0.76	3,385
Buffalo	0.06	-	0.17	0.003	-	0.010	1.43	0.73	942
Charlotte	0.09	-	-	0.003	-	0.018	2.23	0.67	1,046
Chicago	0.06	0.13	0.15	-0.004	-0.002	0.021	1.41	0.60	6,324
Cincinnati	0.07	-	0.08	0.004	0.002	0.010	1.91	0.73	1,549
Cleveland	0.08	-	-	0.006	-	0.009	1.48	0.65	1,637
Columbus	0.05	0.05	0.20	0.005	-	0.011	1.62	0.69	1,288
Dallas	0.02	0.12	-	0.003	0.004	0.014	1.66	0.55	4,058
Denver	-	-	0.32	0.011	0.006	0.017	1.46	0.64	1,785
Detroit	0.03	-	0.07	0.002	0.002	0.008	1.89	0.64	3,524
Hartford	0.15	0.08	-	0.006	0.004	0.007	1.49	0.73	879
Houston	0.05	0.13	0.17	0.002	-	0.015	1.43	0.56	2,968
Indianapolis	-	0.08	-	0.005	0.003	0.017	1.93	0.73	1,065
Jacksonville	0.09	-	-	0.004	-	0.011	1.67	0.63	691
Kansas City	0.09	-	0.10	0.004	-	0.013	1.78	0.74	1,525
Las Vegas	-	0.11	0.09	0.010	0.011	0.014	0.54	0.36	1,270
Los Angeles	0.06	0.12	0.22	0.006	0.004	0.014	1.00	0.44	8,001
Louisville	0.10	-	0.14	0.007	-	0.009	1.99	0.77	929
Memphis	-	-	-	-0.003	-	0.008	1.79	0.62	783
Miami	0.08	0.24	-	0.005	0.003	0.009	0.94	0.37	3,267
Milwaukee	0.04	0.04	0.08	0.007	0.009	0.004	1.78	0.77	1,288
Minneapolis	0.08	0.06	0.10	0.006	0.007	0.014	1.89	0.76	2,309
Nashville	0.07	-	0.07	0.005	-	0.016	2.08	0.72	957
New Orleans	0.12	0.05	-	-	-0.004	0.009	1.43	0.65	1,011
New York	0.09	0.12	0.21	-0.007	-0.005	0.018	1.19	0.75	13,518
Oklahoma City	0.09	0.06	0.11	0.007	0.002	0.012	1.72	0.73	1,021
Orlando	-	0.13	-0.10	-	-	0.015	1.76	0.55	829
Philadelphia	0.11	0.04	0.07	0.002	-	0.013	1.59	0.76	4,181
Phoenix	-	0.14	0.22	0.008	-	0.018	0.93	0.46	2,680
Pittsburgh	0.19	0.05	0.10	-0.004	-0.005	0.014	1.57	0.73	1,902
Portland	0.05	0.08	0.17	0.005	-	0.010	1.71	0.77	1,419
Providence	0.05	0.07	0.09	0.003	0.003	0.004	1.43	0.70	1,194
Raleigh	-	-	0.14	0.005	0.005	0.015	2.22	0.71	564
Richmond	0.10	-0.10	0.11	0.004	0.003	0.008	2.03	0.75	764
Riverside	-	0.43	0.08	0.003	0.003	0.011	0.41	0.52	2,108
Sacramento	-	0.14	0.35	0.008	0.003	0.017	0.78	0.59	1,368
Salt Lake City	-	-	0.36	0.009	0.007	0.018	0.57	0.62	677
San Antonio	-	0.24	-	0.008	0.007	0.012	1.47	0.70	1,302
San Diego	-	0.18	0.26	0.004	0.003	0.013	0.96	0.57	1,784
San Francisco	-	0.05	0.41	-	-	0.020	1.09	0.64	2,885
San Jose	-	-	0.19	0.003	0.003	0.011	1.07	0.45	1,111
Seattle	-	-	0.37	-	-	0.018	1.71	0.65	2,471
St. Louis	0.12	-	0.06	-	-0.002	0.01	1.76	0.70	1,941
Tampa	0.08	-	-	0.003	-	0.014	1.97	0.58	1991
Virginia Beach	0.08	-	-	0.006	0.007	0.007	1.60	0.65	1,123
Washington	0.10	0.06	0.15	-0.005	-0.005	0.025	1.92	0.66	3,483
United States	0.06	0.12	0.16	0.0003	-0.001	0.016	1.53	0.68	108,903

"-": statistically not significant at the 95% confidence level.

Table 4.2: OLS regression model of transit access and equality


a. African American Density Elasticity
Pittsburgh 0.196
Hartford 0.154
St. Louis 0.130
New Orleans 0.125
Philadelphia 0.111
Richmond 0.108
Louisville 0.108
Washington, DC 0.104
Jacksonville 0.098
Charlotte 0.098
Oklahoma City 0.096
Atlanta 0.094
Kansas City 0.093
New York 0.091
Tampa 0.084
Baltimore 0.084
Cleveland 0.082
Virginia Beach 0.082
Minneapolis 0.081
Miami 0.081
Nashville 0.078
Cincinnati 0.073
Buffalo 0.068
Boston 0.066
Chicago 0.064
Los Angeles 0.061
United States 0.061
Portland 0.057
Houston 0.056
Providence 0.052
Columbus 0.051
Milwaukee 0.046
Detroit 0.039
Dallas 0.029
b. Hispanic Density Elasticity
Riverside 0.434
San Antonio 0.241
Miami 0.241
San Diego 0.188
Sacramento 0.149
Phoenix 0.145
Chicago 0.137
Orlando 0.133
Houston 0.130
New York 0.125
Los Angeles 0.125
United States 0.124
Dallas 0.124
Austin 0.111
Las Vegas 0.111
Portland 0.086
Hartford 0.086
Indianapolis 0.083
Birmingham 0.081
Providence 0.077
Minneapolis 0.069
Washington, DC 0.065
Oklahoma City 0.065
San Francisco 0.052
Columbus 0.051
Pittsburgh 0.050
Philadelphia 0.046
Milwaukee 0.041
Richmond -0.107
c. Non-African American, Non-Hispanic Density Elasticity
San Francisco 0.411
Seattle 0.380
Salt Lake City 0.370
Sacramento 0.350
Denver 0.322
San Diego 0.269
Boston 0.241
Los Angeles 0.226
Phoenix 0.220
New York 0.212
Columbus 0.204
San Jose 0.200
Austin 0.189
Portland 0.174
Buffalo 0.174
Houston 0.171
United States 0.166
Chicago 0.152
Washington, DC 0.151
Birmingham 0.150
Raleigh 0.149
Louisville 0.146
Richmond 0.118
Oklahoma City 0.111
Pittsburgh 0.109
Minneapolis 0.108
Kansas City 0.108
Providence 0.099
Las Vegas 0.092
Milwaukee 0.090
Cincinnati 0.089
Riverside 0.083
Atlanta 0.074
Detroit 0.072
Philadelphia 0.071
St. Louis 0.068
Orlando -0.106
d. Low-Income Elasticity
Las Vegas 0.241
San Antonio 0.204
Phoenix 0.195
Denver 0.189
Milwaukee 0.187
Oklahoma City 0.185
Louisville 0.184
Sacramento 0.179
Cleveland 0.174
Salt Lake City 0.159
Baltimore 0.153
Austin 0.148
Indianapolis 0.144
Columbus 0.142
Miami 0.134
Virginia Beach 0.129
Los Angeles 0.128
Hartford 0.126
Nashville 0.123
Jacksonville 0.117
Kansas City 0.109
Raleigh 0.106
Birmingham 0.102
Tampa 0.101
Cincinnati 0.100
Minneapolis 0.100
Richmond 0.097
Portland 0.095
San Diego 0.093
Providence 0.092
Riverside 0.088
Buffalo 0.083
Dallas 0.073
Detroit 0.072
Charlotte 0.072
Houston 0.068
Atlanta 0.063
Philadelphia 0.058
San Jose 0.049
United States 0.007
Boston -0.063
Washington, DC -0.065
Chicago -0.087
Pittsburgh -0.106
Memphis -0.108
New York -0.144

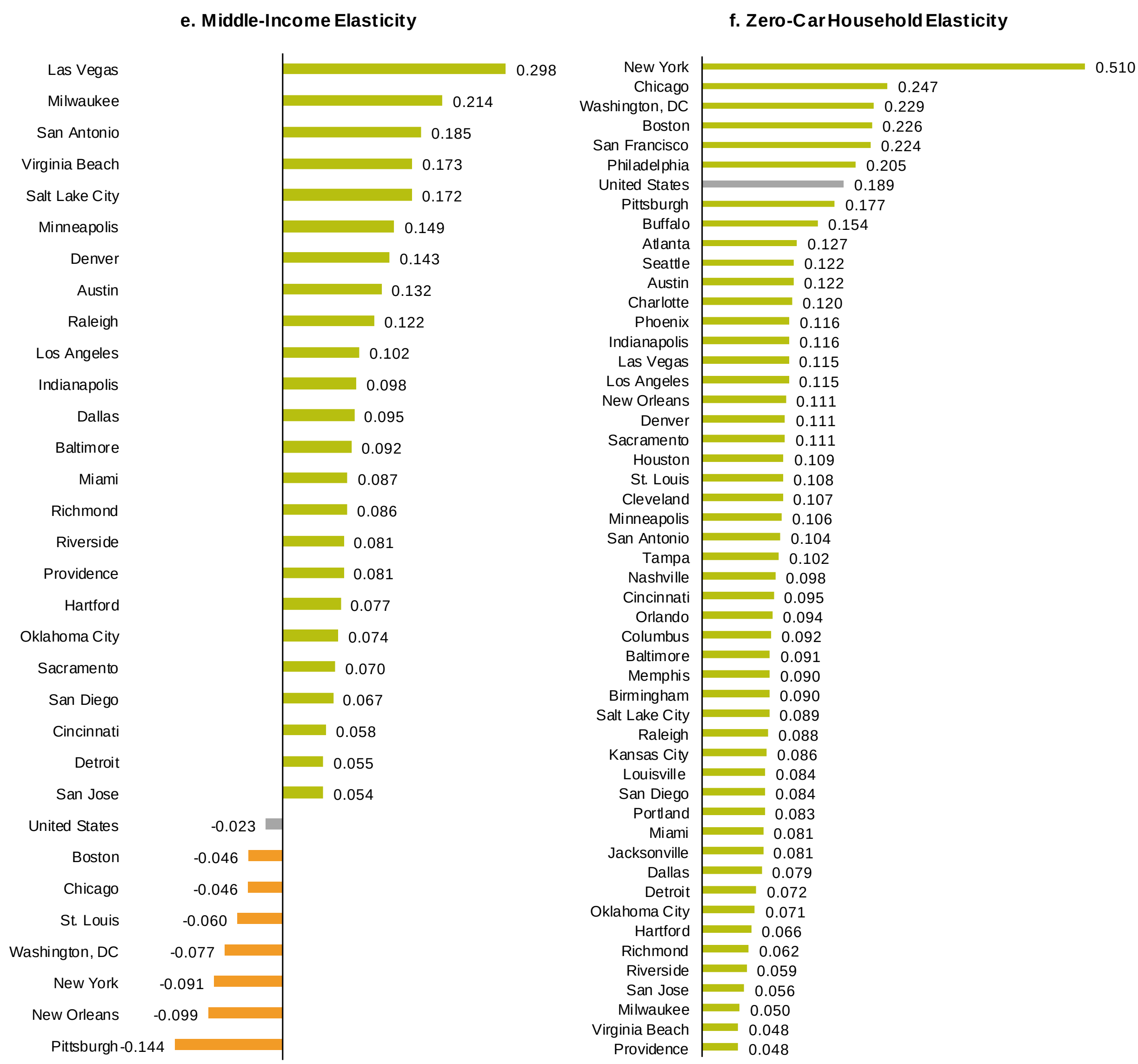


Figure 4.1: Metropolitan regions ranked by elasticities

Our fourth hypothesis (*H*4) was a positive relationship between job access and road network density due to the increased connectivity of the built environment. This relationship was significantly positive for all 50 metropolitan regions investigated in this study. Therefore, *H*4 was corroborated. This correlation was expected, because as road networks become denser, transit services are better able to connect individuals to places of employment.

Overall, the findings show that although major metropolitan areas may excel in providing transit access to one or two socio-demographic populations, they frequently perform below average in providing to other socio-demographic groups. Chicago, for example, is ranked 2^{nd} of 50 in providing access to carless households, 7^{th} of 28 in providing to Hispanics, 17^{th} of 36 in providing to non-African American, non-Hispanic individuals, 25^{th} of 33 in providing to African Americans, 26^{th} of 31 in providing to middle-income households, and 42^{nd} of 45 in providing to low-income households. This type of intra-metropolitan analysis could assist planners in better assessing how to invest in future transit projects. In addition, metropolitan transport planners could use this study to determine how their region compares to others. For example, to compare Minneapolis and Portland, we find that transit access in Minneapolis exceeds that in Portland in terms of African American population density, low-income households, and carless households. Conversely, transit access in Portland exceeds that in Minneapolis in terms of Hispanic population density and non-African American, non-Hispanic population density. This kind of inter-metropolitan analysis could help illuminate possible areas of improvement for regions desiring to increase the equality of their transit access to ensure that all groups are served fairly by the public transit system. None of the 50 largest metropolitan regions ranked above the national average in all seven categories, nor did any rank below the national average in all seven categories. Most importantly, to achieve equal access, it is essential to improve transit access for any disadvantaged socio-demographic group that experiences a negative correlation with job access so that all individuals may receive equal access to opportunities regardless of race, income, age, gender, or disability. Because of spatial segregation, whatever the cause, given a finite amount of service, service to one area may substitute for service to another area. For instance, relatively more transit in low-income areas comes at the cost of relatively less transit service in non-low-income areas, many

of which are middle-income. Similarly, relatively more service in an African American area comes at the cost of relatively less service in a non-African American area, which may include Hispanic neighborhoods. So understanding both relative and absolutes is essential to grasp the full picture.

We note there are alternative interpretations. Ensuring uniform transit access across space is essentially impossible. By focusing service on community X, community Y will receive less. Metropolitan areas with, say, better than average bus service for minority populations may thus stigmatize transit service as being predominantly for that ethnic minority, which could reduce its broader political support. Many metropolitan areas have faced the dilemma. To broaden the base of support, and in the name of "spatial equity," many communities spend scarce transit operating budgets providing services to whiter suburban areas where it is more expensive per ride.[17] This is obviously not a good solution, but is widely used.

[17] (Taylor 1991).

Conclusion

This chapter ranked the 50 largest metropolitan regions in the US in order of how well transit access serves each socio-demographic group. By including the results of the national model among the metropolitan rankings, it becomes apparent at a glance whether a region is performing above or below the national average in any given category. The use of elasticities permits a direct comparison of access by transit within and between metropolitan areas. For example, although no metropolitan regions show a statistically significant negative correlation between the population density of African Americans and job access, it can be observed that Dallas serves this socio-demographic population half as well as the national average, and New Orleans serves this population twice as well as the national average. San Francisco provides transit access to Hispanic populations half as well as the national average, while San Antonio provides transit access to this population twice as well as the national average. While in Columbus transit access for African American and Hispanic communities is below the national average, it provides a level of access above the national average to non-African American, non-Hispanic individuals. This ability for intra-metropolitan comparisons, as well as inter-metropolitan comparisons, offers a better understanding of which

socio-demographic groups are best provided with transit access. This breakdown is important for obtaining a more detailed understanding of transit access to jobs across the nation. For example, although New York is ranked 1st in providing transit access to carless households, it is ranked last in providing access to low-income households. Although Pittsburgh is ranked last in providing transit access to middle-income households, it is ranked 1st in providing access to African Americans. These findings exemplify how a single access score for an entire metropolitan region may gloss over these socio-demographic distinctions that are critical to transport equity. Important findings are also revealed by combining inter- and intra-metropolitan analyses. For example, four major metropolitan regions show statistically significant negative correlations between access and both low- and middle-income households, as well as very high statistically significant positive correlations between access and percent carless households. These findings indicate that these four regions (New York, Chicago, Washington, and Boston) provide the best transit-based job access to high-income, carless households. While this finding may speak to the relatively high-quality of public transit available in these major urban areas, it does not reflect as well on the equity of the transport systems.

Next

The first limitation of the present study is that of endogeneity, which refers to the joint determination that might exist between location of residence and location of employment, since both contain elements of self-selection, and both may be driven by the same unobserved personal characteristics. The results of this stud cannot be used to determine whether transit systems are designed to serve disadvantaged socio-demographic groups or if certain socio-demographic groups are moving to areas with higher transit access already in place. Of course, this analysis alone cannot be used to study causation. Rather its purpose is to facilitate a discussion about trends in equity of transit access across the nation. To address the concern of endogeneity, future work will consider longitudinal data sets to analyze changes in job access over time in terms of select socio-demographic populations.

The second limitation of this work is related to the access measure, which considers all jobs equally when realistically not

every resident is qualified for every job. For example, a low-income neighborhood might find great transit access to many white-collar jobs but would not necessarily benefit most of the residents living in that neighborhood if low-income and high-income jobs are in different locations. However, despite these two limitations, it can still be concluded from this study that transit access is not equally distributed among all socioeconomic groups across all of the largest 50 metropolitan regions in the US. Careful consideration of disadvantaged socio-demographic populations during transport planning and policy-making is required to reduce the disparity in access to opportunities provided to individuals by race, income, age, gender, or disability.

5
Access During COVID

James DeWeese, Kevin Manaugh, and Ahmed El-Geneidy

Abstract: This chapter shows how access can be used as a rapid diagnostic tool to assess the potential impacts of public-transport service adjustments during a public-health crisis. We examine access changes to a range of job and activity types resulting from the service alterations the greater Montréal region's public-transport operators made in response to COVID-19. Using publicly available data and free software, we find that access to many jobs classified as 'essential' declined more severely than nonessential jobs. We also find that the public transport service changes that took place between May 2019 and May 2020 in Montréal significantly reduced the number of health-sector workers who could reach some area hospitals within 45 minutes by transit at key shift-change times. Although this chapter focuses on using access to analyze public transport operators' responses to a unique health crisis, it may also be of interest to practitioners wishing to incorporate equity analysis into their planning processes more generally as it suggests a quick and straightforward method to assess access by public transport for defined groups.

Introduction

Keywords: Access; Equity; Public transport; Public transit; COVID-19; Service cuts

The COVID-19 pandemic posed unprecedented challenges for public transport agencies forced to balance their response to precipitous declines in ridership with their central role as an essential public service for frontline workers and others. As the pandemic spiked in April 2020, for example, public bus ridership on Montréal's primary operator fell by 82 percent; Metro ridership was down 92 percent during the same time.[1] Even as public transport agencies curtailed or

[1] (CBC News 2020).

[2] (Bartik et al. 2020).

canceled services, however, many low-wage workers had no choice but to travel, raising important questions of equity.[2]

In this chapter, we explore how access to so-called essential and nonessential jobs and services evolved during the spring of 2020 due to service changes in Montréal. We also assess how health facilities' access to healthcare workers changed during this period. Using readily available census data and open-source software, we demonstrate a methodology that public transport agencies – even those with limited resources – could adopt to evaluate quickly and cheaply potential service adjustments in response to future crises, including public-health emergencies or natural disasters. Although this chapter focuses on using access to analyze Montréal public transport operators' responses to a unique health crisis, it may be of interest to practitioners wishing to incorporate equity analysis into their planning processes more generally as it suggests a quick and straightforward method to assess access by public transit for defined groups.

Questions

The animating goal of this chapter is to show how access might be calculated and used by policymakers and practitioners to quickly identify and communicate the projected impacts of public-transport service adjustments during an emergency. The methods described here are not intended to definitively assess the appropriateness of particular service adjustments. Nor could they be relied on to dictate possible alternatives. Instead, they represent a means to conduct a quick diagnostic assessment of potential impacts as a predicate to more detailed analyses relying on fewer simplifying assumption and more specialized data if necessary.

This chapter addresses the following questions:

- How did public-transport service adjustments in response to COVID-19 affect access to jobs and services in the greater Montréal region and how were these changes in access distributed spatially, temporally, and socio-demographically?

- How well did these service adjustments in response to COVID-19 preserve access to those jobs and services deemed essential during the pandemic?

- How specifically did the service adjustments affect access to health-related opportunities for the general public and the potential availability of health-sector workers for hospitals?

Methods

With a population of more than 4 million in 2016, Montréal is the largest city in Quebec and one of the largest in Canada. The region possesses an extensive, well-used, and mature multi-operator public transport-network including metro, bus, and commuter-rail service. We elected to conduct a year-over-year comparison of access to help control for seasonal service adjustments. By May 2020, Montréal had experienced its deepest COVID-related public-transport service cuts. For this comparison, we therefore selected May 8, 2019, and May 13, 2020, which represent typical, nonholiday weekdays.

Access can be measured in numerous ways with varying degrees of complexity and sophistication. Here, we use the simplest measure: Cumulative Opportunities Measure.[3] This measure sums the number of destinations a person can reach from a given origin within a defined time or distance. Though this metric does not account for the relative attractiveness of destinations that are closer, it has the distinct advantage of being easily communicated and understood, making it an obvious choice for quick calculations to help shape policy decisions. For our analysis, we selected a 45-minute travel-time cut-off to align with the average commute in Montréal.

[3] See chapter 1 in this volume.

Widely available standardized transit data in the form of General Transit Feed Specification (GTFS) schedules and the proliferation of user-friendly and intuitive open-source software tools has rendered the calculation of access more "accessible."

The first step in the calculation of access is to obtain information about the transport network and the people, locations, and opportunities it links. For our origins and destinations, we use the geographical center, or centroids, of census tracts. To identify the opportunities or activities available at each destination, we relied primarily on home-to-work travel flows from Canada's 2016 census. These data include the number of people from each census tract traveling for work to every other census tract and are broken down by job categories as defined by the North American Industry Classification System (NAICS). To calculate available opportunities at any given destination, we simply summed the number of work

trips for each job category terminating in each census tract throughout the region. These work destinations perform double duty: They are employment locations for the workers traveling to them and also serve as a convenient proxy for the various types of services that may be available to the public at a given location.

To obtain these home-to-work flows, broken down by job category, the researchers had to pay Canada's statistics agency, Statistics Canada, for a special extraction. In other jurisdictions, however, similar types of data may be available for free, although not necessarily with the level of specificity required to analyze changes by detailed job category. For example, the US Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) data contain home-to-work flows broken down by worker age, broad salary ranges, and general job category. The LEHD data are available for free from the Bureau's Web site and through other free and open-source software packages. Other options to obtain "opportunities" data include information from OpenStreetMap, a freely available, volunteer-edited mapping service that can be accessed using a variety of tools. Here, we used OpenStreetMap data to identify the locations of hospitals.

For information about the transport system, including the road and pedestrian network and transit service schedules, we relied on free, broadly available sources. Our road network came from OpenStreetMap downloaded from the GEOFABRIK regional extracts survey. Our transit schedules for both study periods May 2019 and May 2020 were downloaded from OpenMobilityData, formerly known as Transit Feeds.[4] OpenMobilityData offers an archive of historic transit schedules in the widely adopted General Transit Feed Specification (GTFS). The GTFS can be browsed and downloaded manually or, as we did here, a simple software script can be created to identify and download the relevant schedules programmatically.

[4] (OpenMobilityData 2021).

Calculating access also requires tools to estimate the ease of reaching given destinations. In the past, it was already relatively easy to calculate travel times or distance for single-mode trips by car, bicycle or on foot, between various points using GIS software such as QGIS. Multi-modal travel, especially with public transport, was far more difficult to route over a network and often required expensive and/or complicated private software. Major advancements in powerful, open-source tools have largely erased this challenge.

For this analysis, we rely on *R*, an open-source programming language that benefits from a worldwide network of contributors who produce freely available add-on software packages with an enormous range of functionalities. Many of these packages assist with transport analysis.

Two, in particular, are relevant to transit-based multi-modal trip routing: opentripplanner and the more recently developed *r5r*. Here, we used *r5r*, which allows users to "drive" Conveyal's java-based R5 routing engine from within *R*, making it substantially easier for nonprogrammers to deploy this powerful and fast tool to calculate matrices of travel times between all origins and destinations over a public-transport network.[5] Using *r5r*, we calculated travel time-matrices for various times of the day based on typical peak and off-peak travel. For our more detailed look at health workers' access to hospitals, we also calculated travel times coinciding with typical shift changes for facilities in the Montréal region. Finally, to understand one aspect of the potential equity impacts of public transport service adjustments, we downloaded and mapped census tract median household income data from Canada's 2016 census using the cancensus *R* package.[6] Cancensus offers users an easy and intuitive way to directly census data and geographic boundaries – already linked – directly into *R* for immediate use. Similar packages are available for US Census data and other jurisdictions. Table 5.1 provides a brief overview of the main packages and data sources on which we relied.

[5] (Pereira et al. 2021).

[6] (von Bergmann et al. 2021).

Findings

Access across the Montréal region

Access to jobs and other destinations of interest declined most significantly during the early-morning hours, illustrating that transit agencies made deeper cuts during these peak times (See Figure 5.1). As the maps illustrate, more census tracts experienced year-over-year declines in overall access to job opportunities during the 7:00 AM peak than during later hours of the day. The most severe declines in access took place across suburban regions, such as Laval and Longueuil, off the Island of Montréal.

Without detailed knowledge of transit operators' scheduling and response, it is difficult to completely isolate COVID-related adjustments and their impact. We elected to measure changes in

R	
cancensus	Search for and download ready-to-use Canadian census data and geographies
osmdata	Download points-of-interest, such as retail stores or hospitals, from OpenStreetMap
r5r	Quickly calculate travel matrices for all origins and destinations over a public-transport network using Conveyal's java-based R5 routing engine .r5r requires GTFS public-transport schedules and .pbf-format street networks from OpenStreetMap.
Data Source	
Statistics Canada – 2016 Home-to-Work Travel Flowsby Job Category	Home-to-work flows, which show the number of people traveling between different origins and destinations, allow researchers to identify the number of "opportunities," such as jobs or services provided by workers that exist at any given destination. (Available for purchase from Statistics Canada)
GEOFABRIK OpenStreetMap Data Extracts	The free server offers downloadable extracts of complete OpenStreetMap data for different areas, ranging from whole continents to national sub-regions. The data can be downloaded in the .pbf format required by *r5r*. Command-line software is available to trim the sub-regional OpenStreetMap data to the study area to reduce computation time.
OpenMobilityData (formerly Transit Feeds)	Online repository of historical GTFS-format public transport schedules from operators around the world.

Table 5.1: *R* packages and data sources used in this analysis

access from May to May to control for potential regular seasonal schedule changes that might have occurred between the onset of the pandemic's widespread impacts in March 2020 and spring 2020, when transit agencies began to enact some of the most significant changes in their schedules. As expected, many census tracts actually experienced year-over-year increases in access, shown in light green in the maps in Figure 5.1. These increases likely stem from service adjustments unrelated to the transit agencies' response to COVID-19.

It is conceivable – even likely – that these areas of year-over-year access improvements actually witnessed declines relative to the beginning of the pandemic. Decision makers could further explore this possibility by conducting the same analysis on a month-to-month basis. For our analysis, however, we determined that declines in access year-over-year, reflecting greater difficulty in traveling by transit, would be of greater relevance to policymakers and operators.

The juxtaposition of areal socio-demographic information and changes in transit-system performance offer policymakers and transport operators an opportunity to explore and highlight the impacts of service adjustments on equity. Here, we see that morning reductions in access largely occurred outside the region's poorest census tracts, as measured by median household income. This is particularly important because lower-income groups are frequently more reliant on public transport. The black outlines in the maps in Figure 5.1 show the census tracts from the lowest household-income decile. Across most of the Island of Montréal, census tracts in this income decile experienced relatively minor reductions in average transit-based access year over year, with the vast majority ranging from 0% to 5%. Some lower-income census tracts on the Island of Montréal and in Longueuil recorded year-over-year improvements in access. The maps also allow us to easily pinpoint areas that may deserve additional scrutiny. In south eastern areas of Laval and northern and eastern areas of the Island of Montréal, there are a handful of lower-income census tracts that saw greater-than-40% decreases in access during the morning travel hours.

Median household income offers just one of a vast range of possible metrics to assess the equity impacts of service adjustments. The selection of the most appropriate measures will depend on a mix of considerations unique to different populations, policymakers and operators. But easily obtainable census information, such as age, gender, income, education levels, and immigration status – alone or in combination – offer numerous potential options. Many ready-made, publicly available indicators of social deprivation also exist. These areal summary measures elide important differences among individuals within populations and can thus mask very real discrepancies in transport systems' usefulness and usability for different people. They cannot therefore serve as a substitute for more granular knowledge about transport systems' user populations. But they can be extremely useful in quickly exploring and communicating potentially problematic outcomes from proposed service adjustments.

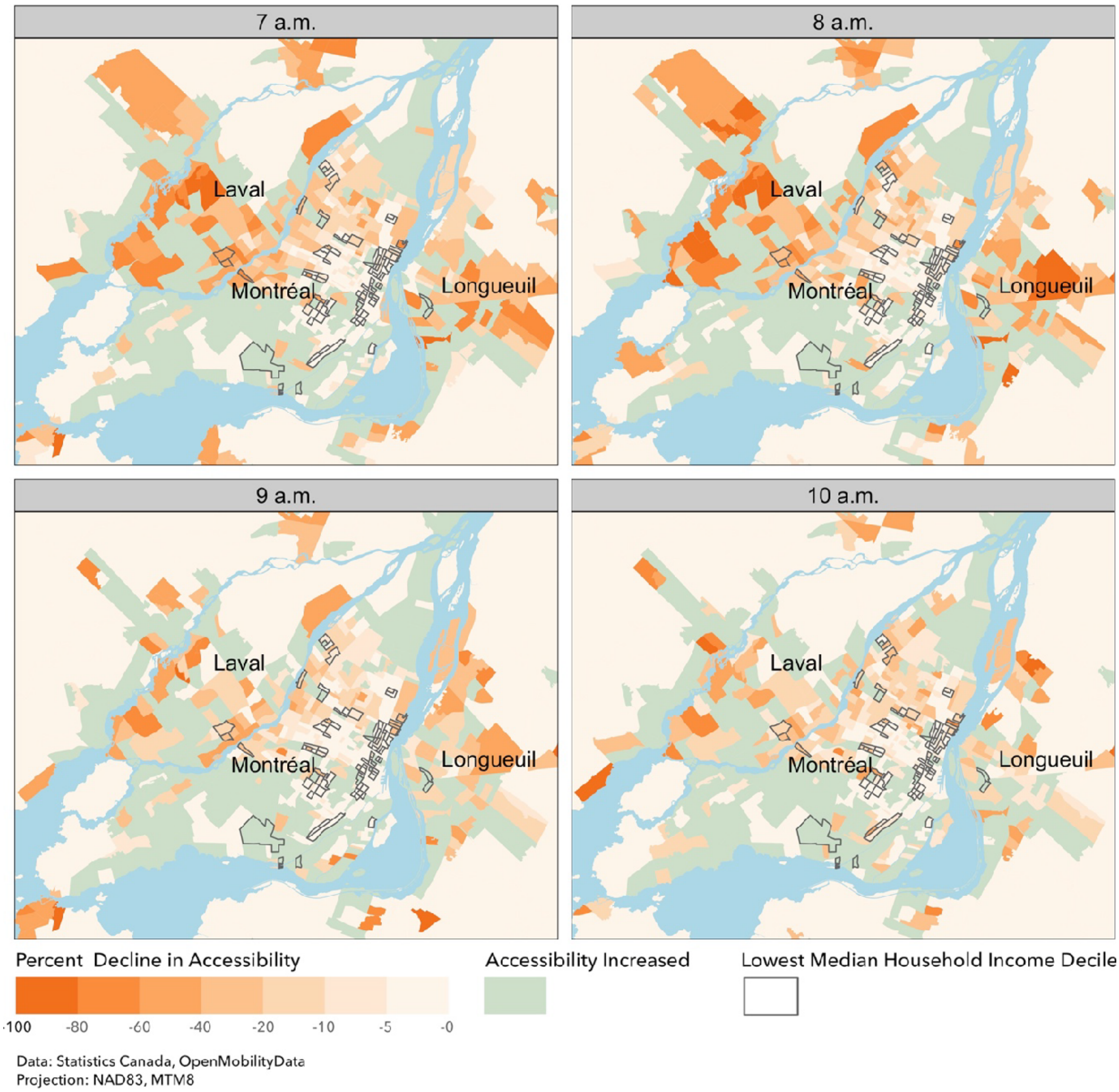


Figure 5.1: Change in access in 45 minutes by public transport to all jobs

Access across job categories

As part of the region's pandemic response, businesses and services were broadly classified into those that were essential and those that were nonessential. In most cases, essential business and services were allowed to remain open and required in-person operation. Essential businesses included certain retail locations, such as grocery stores; many healthcare facilities; some wholesale operations; and at various times, construction. Nonessential businesses were largely shuttered or were able to operate with employees working remotely, eliminating the need to travel. These included, financial services offices, for example. One potential measure of a public-transport systems' efficiency during the pandemic, then, is to examine the extent to which necessary service adjustments preserved access to essential businesses and services for both workers and the general public. The work-to-home census data we used to generate our "opportunities" data set defines jobs by commonly used categories, allowing us to consider the relative changes in average access to essential and non-essential destinations.

We find that in the Montréal region, service adjustments, particularly during the early-morning hours – travel to essential jobs and services may have actually been more negatively affected than travel to nonessential locations. For workers departing at around 7:00 AM, average access to jobs in their sectors declined by about 5% to 13%, as shown in Figure 5.2. The categories where declines were most severe included construction, health, manufacturing, and wholesale operations. During the later-morning period, the range of declines for all job categories compresses and clusters around an approximate 5% drop in average access.

A similar pattern exists for population-weighted access to opportunities across categories, as shown in the lower panel of Figure 5.2. Although the gap between access to essential and nonessential services is smaller, declines in access to essential categories of businesses are consistently greater at 7:00 AM Construction, health, manufacturing, retail and wholesale categories all experienced declines in average access of more than 10%. No systematic difference between those destinations that were considered significantly different for different types of opportunities. Over the morning, the range becomes more tightly compressed.

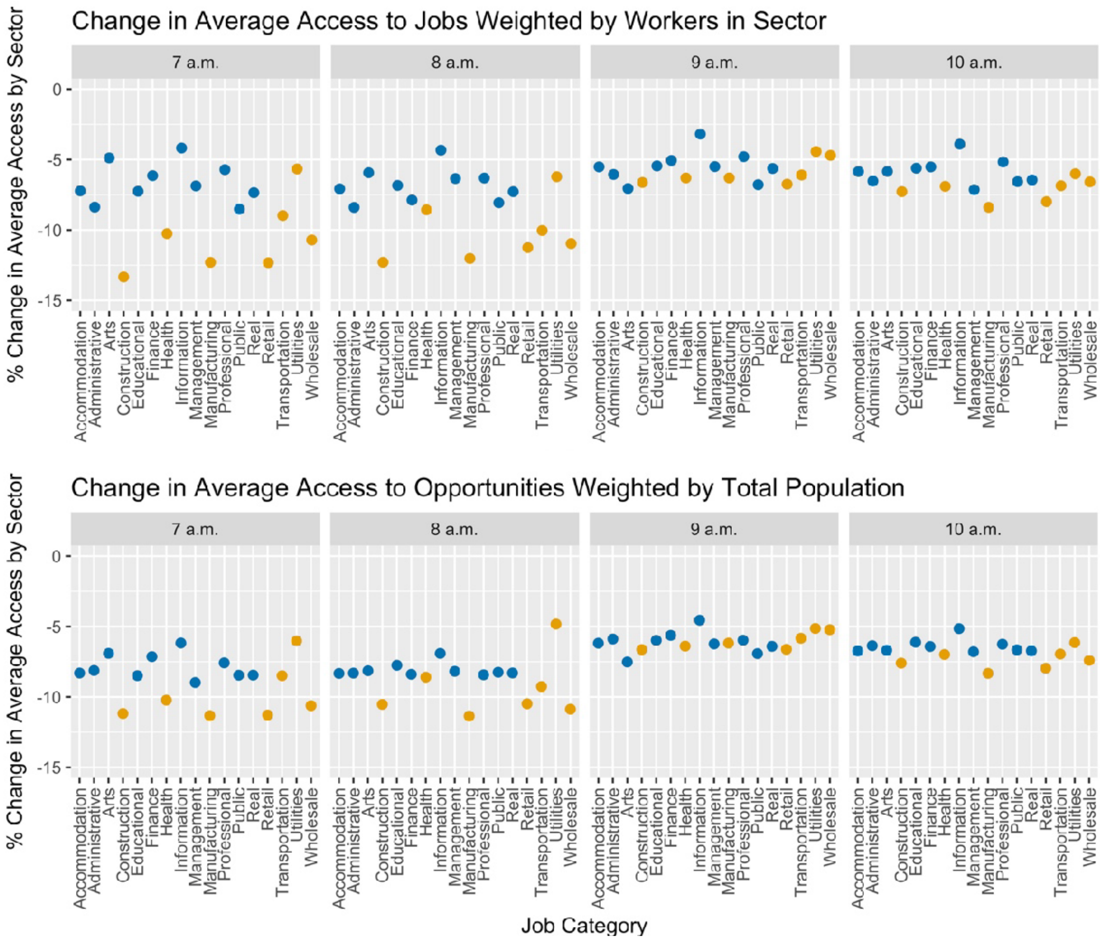


Figure 5.2: Percent changes in average access across job categories. The upper panel shows changes in average access weighted by the number of workers in each category. The lower panel shows changes in average access weighted by the total population experiencing those changes.

This quick diagnostic review of system performance suggests that service adjustments were not necessarily calibrated to preserve access to essential rather than nonessential functions. If they were, declines would be expected to be less severe for categories deemed essential.

In some cases, it may not be possible to make precisely target different categories of access. For example, some categories of jobs or destinations, such as retail, may be more spatially dispersed than management or manufacturing jobs. In other cases, certain types of destinations may routinely co-locate with others. Access to one would necessarily mean access to the other. To determine whether this may have occurred here, we examined the correlation between different categories of employment within census tracts. Figure 5.3 shows the results.

Figure 5.3: Percent changes in average access across job categories. The upper panel shows changes in average access weighted by the number of workers in each category. The lower panel shows changes in average access weighted by the total population experiencing those changes.

While many categories show strong correlation with one another, some of the designated essential businesses do so to a lesser extent. Health, in particular, demonstrates very little correlation with other opportunity categories. This suggests that it could be at least theoretically possible to more precisely target service adjustments to preserve access to health-related facilities for both workers and the general population. The actual ability to do so, however, depends not just on the dispersion of the facilities themselves but also on the residential or origin locations of the people who desire to reach them.

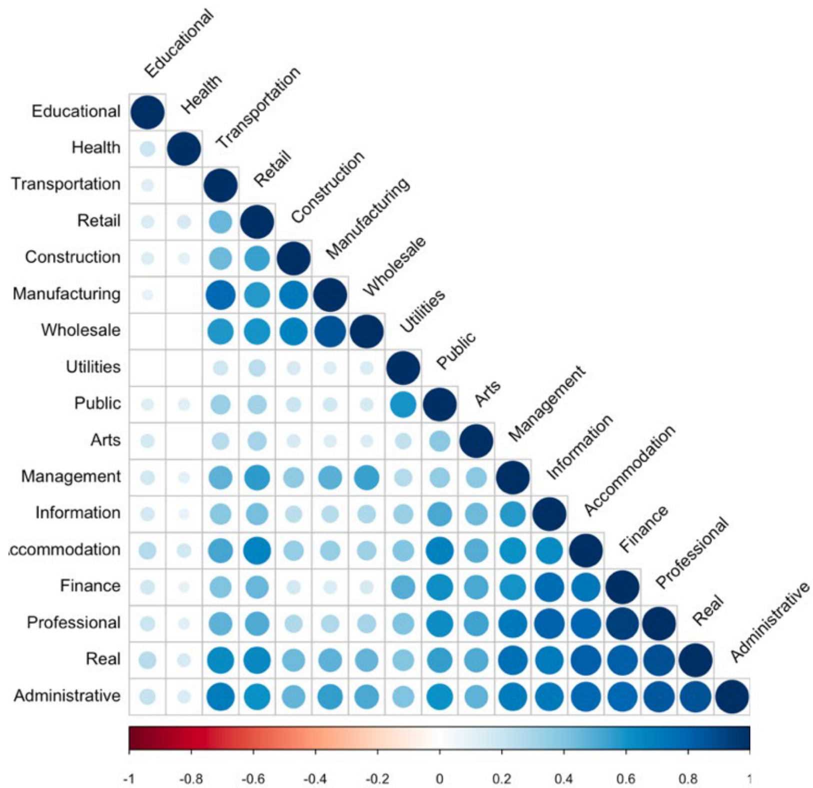


Figure 5.4: Correlation between the number of jobs by census tracts

Access to health facilities

Changes in access to health-related opportunities specifically reflect a similar temporal, spatial and socio-demographic pattern to changes in access to all types of opportunities. The largest reductions in access take place during the early-morning hours in suburban, off-island areas and largely avoid the lowest-income census tracts (See Figure 5.4). By later in the morning, reductions in access to health-related opportunities are much less acute posing fewer potential challenges to members of the general public seeking care who may be considered less likely than healthcare workers to travel in the early-morning hours.

Visualized differently, the same travel and access data demonstrate the potential challenge from the perspective of hospitals which rely on public transport to consistently ferry healthcare workers to and from the facilities. The maps in Figure 5.5 show the change from May 2019 to May 2020 in the number of

health-sector workers able to reach hospitals and other major health facilities within 45 minutes using public transport. Travel times were calculated for departures around 7:00 AM, 3:00 PM, and 11:00 PM to align with typical shift changes in Montréal-area hospitals, which generally occur at 7:30 AM, 3:30 PM and 11:30 PM. For the first shift, two hospitals saw the number of health-sector workers able to reach them within 45 minutes by transit decline by more than 55% year over year. Another eight hospitals experienced declines in access by workers of between 15% and 25% at 7:00 AM. In many cases, the hospitals experiencing the greatest declines in worker access varied over the course of the day.

This approach to measuring access differs from our earlier analysis, which focuses on the number of opportunities individuals could reach, and instead identifies the number of workers potentially available to specific facilities. This general measure of worker access does not necessarily mean employees of a particular hospital will definitely experience difficulty arriving at work since it does not account for actual mode choice or specific hospital-location/employee-residence pairs. It may, however, serve to help transit operators and even hospital officials quickly identify highlight potential challenges. In the case of hospital administrators, reviewing these sorts of potential impacts from public transport service adjustments could encourage them investigate further by directly polling workers and, when necessary, deploy alternative travel arrangements.

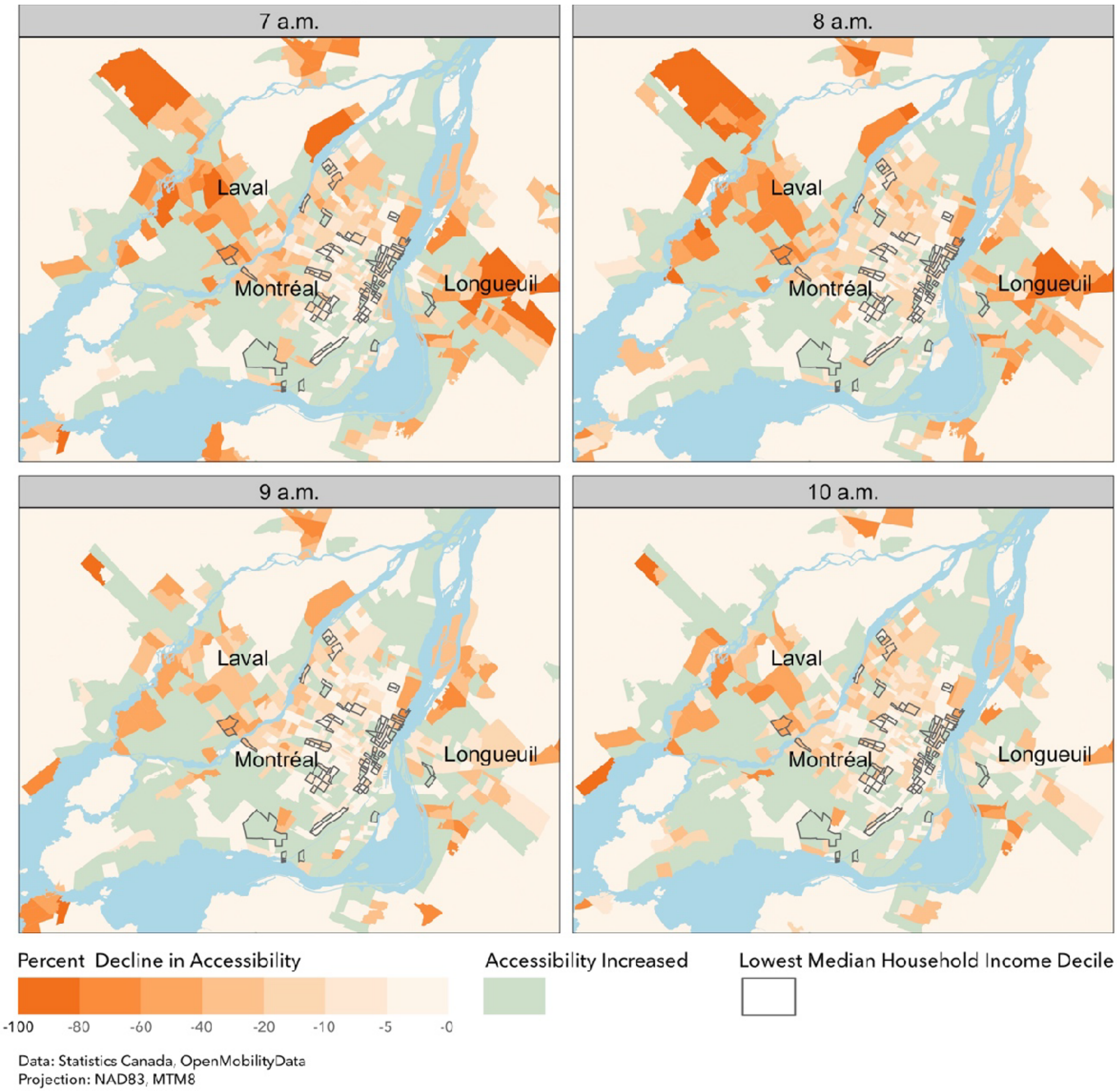


Figure 5.5: Change in access to health-related facilities within 45 minutes by public transport

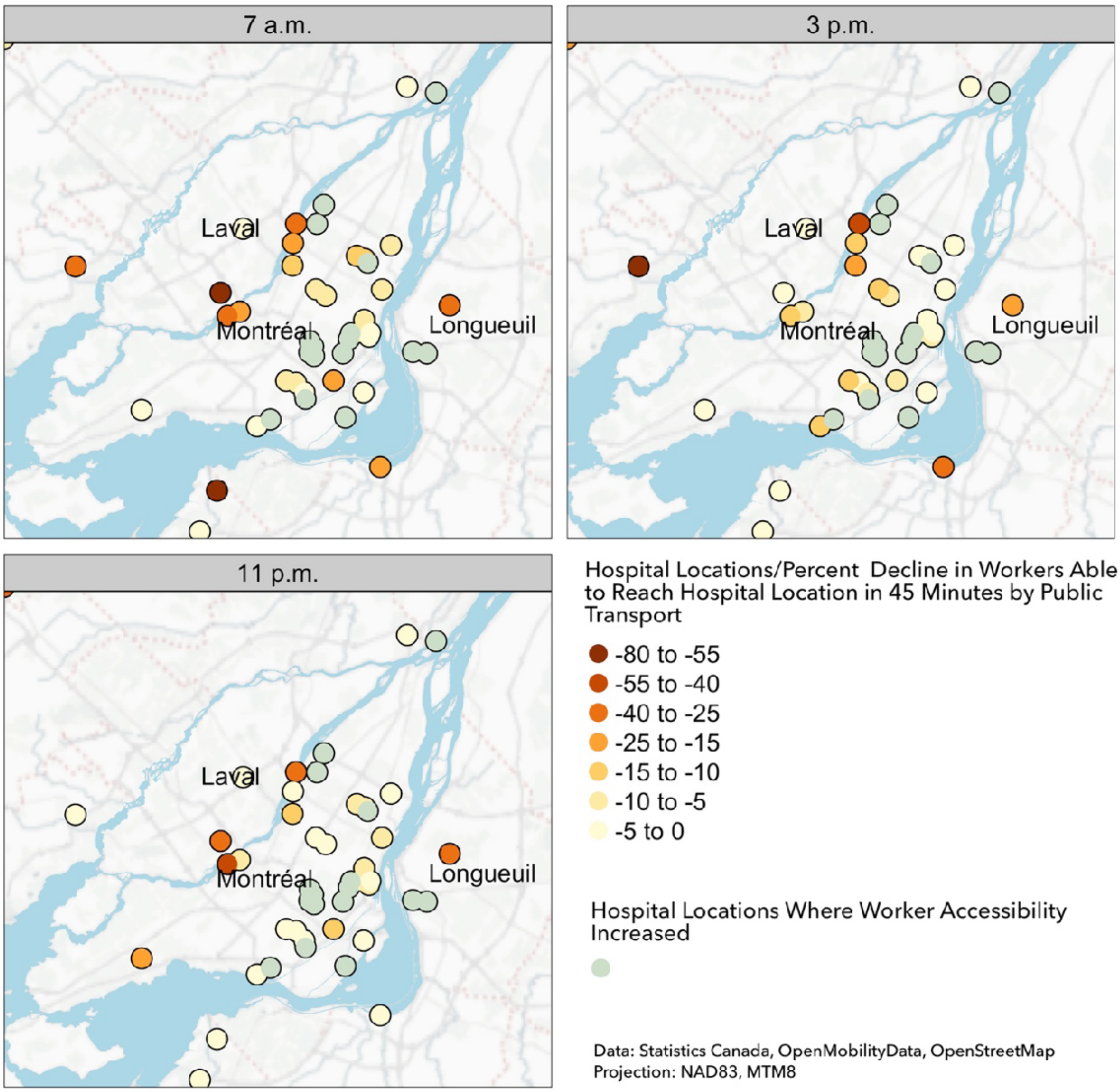


Figure 5.6: Percent change in health-sector workers able to reach hospital locations in 45 minutes by public transport

Conclusions

The objective of this type of access 'quick check' is to offer a quick and relatively easy methodology to help policymakers determine whether more in-depth analyses should be conducted of proposed or implemented service adjustments. It necessarily relies on a number of simplifying assumptions. For example, the work-to-home travel information we rely on to identify job/business destinations for this analysis does not include actual time-of-departure information. For purposes of this analysis, we assumed that the total number of jobs or other destinations available at a particular location throughout the day is correlated to some extent with jobs/destinations that might be available at particular times. It is, therefore, impossible to know for certain how severely workers or others might have been affected by the service adjustments at any given hour.

For these reasons, this diagnostic cannot tell policymakers and transit officials precisely how to navigate the multitude of financial, economic, humanitarian, and political considerations that shape emergency responses. Nevertheless, it may help them more readily identify and communicate the need for more detailed analyses that ultimately suggest more nuanced approaches to service adjustments in response to public health or other emergencies.

Here, the results suggest the possibility that access to essential locations might have been more severely compromised by COVID-related service adjustments than access to less important destinations.

Next

Access to this type of information could allow policymakers and transit operators to explore alternative adjustments or to proactively communicate with groups or organizations that might be affected, allowing them to consider their own alternatives. The easy generation and communication of these types of access calculations also render it easier for potentially affected groups or organizations to conduct their own analyses and advocate on their own behalf.

Enhancements in publicly available data and dramatic improvements in the functionality of freely available and relatively easy-to-use technology mean that access measures can be more broadly deployed by a wider range of people. The increasing

acknowledgement of access as a meaningful, easily calculated, and communicated measure will see its adoption in new situations, including as a way to quickly pinpoint potential impacts of transport operators' responses to public health or other emergencies.

6

Access to Shelters

Mahyar Ghorbanzadeh, Kyusik Kim,
Eren Erman Ozguven, and Mark Horner

Abstract: This chapter assesses the spatial access of US census population block groups to congregate and non-congregate shelters in Northwest Florida. The closest facility and the two-step floating area (2SFCA) methods are applied, and the Access Index (AI) and Access Ratio Difference (ARD) are defined to compare the spatial access of each census block group based on the utilized approaches. Results reveal that people in coastal areas where a higher number of lodging facilities are located have better access. Considering the capacity of each facility shows that many areas in Northwest Florida have lower access to lodging establishments than emergency relief shelters. The knowledge obtain from this chapter provides practical information and insights for identifying vulnerable areas. This should raise the awareness of the need to provide better access to non-congregate shelters in the case of sheltering during co-occurring disasters such as the COVID-19 pandemic and hurricanes.

Introduction

Keywords: Spatial access; Hurricane; COVID-19 pandemic; Social distancing; Congregate shelters; Lodging establishments

Among the natural hazards recorded in the US history, hurricanes have caused the most deaths and widespread destruction, particularly in coastal areas.[1] Florida is especially vulnerable to hurricanes due to its unique geography and extensive coastlines.[2] Due to these hurricanes, many Floridian communities and specifically those along coastal areas are required to evacuate to safer places such as emergency shelters. Therefore, shelters in Florida play a role in meeting the needs of their communities and

[1] (National Oceanic and Atmospheric Administration (NOAA) 2020, Zhu et al. 2020).

[2] (Sobanjo et al. 2013).

providing services to the public. Ensuring spatial access to these facilities is essential.

Transport access assessment to shelters and emergency facilities has been widely studied in the literature.[3] A considerable number of studies have focused on assessing the transport-based access to critical facilities such as shelters[4] and healthcare facilities.[5]

The access to healthcare facilities in rural Ghana was used to identify the areas with low, moderate, and high level of access.[6] The spatial access to emergency response facilities including police stations, fire stations, and hospitals using real-life hurricane-related roadway closure data due to Hurricane Hermine has also been assessed.[7] More recently, an assessment of people's spatial access to mental health services in Florida revealed that population block groups and rural counties which are mainly located in Northwest Florida have poor access to these facilities.[8] There are growing number of studies dealing with the transport-based access to critical facilities during the COVID-19 pandemic, such as spatial access of COVID-19 patients to healthcare resources focusing on Illinois.[9] An investigation of transport access's role during the COVID-19 pandemic in Italy showed a positive correlation between the access and number of COVID-19 cases in an area.[10] Another effort measured the spatial access to COVID-19 testing sites at the census tract level in Florida via the 2SFCA method.[11] Most of the tracts located in rural areas, people without access to cars, and the aging population (65 years old or above) had the lowest level of access to testing sites in the state.

Providing access has been even more challenging since these communities were hit by the COVID-19 pandemic during the hurricane season, thereby restricting shelter capacity due to social distancing requirements. The Centers for Disease Control and Prevention (CDC) indicate that it is potentially hazardous to use congregate shelters.[12] On January 20, 2021, the World Health Organization (WHO) announced approximately 95 million confirmed cases and more than 2 million deaths due to the COVID-19 pandemic globally.[13] On this date, the CDC recorded more than 400,000 deaths due to COVID-19 in the US, and this number is still increasing rapidly.[14] As of January 20, 2021, Florida, with 1,601,011 positive cases and over 24,000 deaths, ranked third among the US states after California and Texas.[15]

This capacity challenge can be addressed by the use of alternative non-congregate shelters (i.e., lodging establishments such as hotels

3 (Akhavan et al. 2018, Horner et al. 2015).

4 (Kocatepe et al. 2019, Unal and Uslu 2016).

5 (Ermagun and Tilahun 2020, Khan 1992, McGrail and Humphreys 2009).

6 (Agbenyo et al. 2017).

7 (Kocatepe et al. 2016).

8 (Ghorbanzadeh et al. 2020).

9 (Kang et al. 2020).

10 (Cartenì et al. 2021).

11 (Tao et al. 2020).

12 (Centers for Disease Control and Prevention (CDC) 2020b).

13 (World Health Organization (WHO) 2020).

14 (Centers for Disease Control and Prevention (CDC) 2020a).

15 (Florida Department of Health 2020).

and motels). These are recommended by the Federal Emergency Management Agency (FEMA) in order to protect public health and limit general population sheltering.[16] Understanding to what extent these lodging establishments are available in the case of non-congregate sheltering during an uncontrolled outbreak such as COVID-19 is a policy question related to transport access that has yet to be considered.

[16] (Federal Emergency Management Agency (FEMA) 2020).

Questions

This chapter focuses on measuring the spatial access to congregate and non-congregate shelters simultaneously in vulnerable areas to hurricanes during a disaster such as the COVID-19 pandemic. In particular, it addresses the following question:

- What happens if a hurricane affects a vulnerable area during a global pandemic such as COVID-19 and the residents want to evacuate to non-congregate shelters (i.e., lodging establishments) rather than regular shelters due to social distancing requirements recommended by the CDC?

In order to answer this question, this chapter assesses the spatial access of US census block groups to the congregate and non-congregate shelters in Northwest Florida using both the closest facility and the two-step floating catchment area (2SFCA) methods.

The closest facility method is applied to compute travel times to the nearest facility using the optimal path between census block groups' centroids (origins) and the facilities (destinations) using the road network. The 2SFCA method is used to obtain the high and low access areas in Northwest Florida given the number of people in each census block group (demand) and capacity of facilities (supply). In addition, the access Index (AI) is used to compare the spatial access of census block groups to the facilities given the obtained travel times between them, and the access Ratio Difference (ARD) to compare the level of access obtained by the 2SFCA method to these facilities for each block group.

Methods

Study area

This section focuses on describing Northwest Florida (the Florida Panhandle) as it serves as our case study application. It was hit hard by recent destructive hurricanes namely, Hurricanes Hermine, Micheal, and Sally.[17]

[17] (Berg, Robbie 2017, Beven et al. 2019, National Weather Service (NWS) 2020).

- Hurricane Hermine was a Category 1 hurricane that made landfall on September 2, 2016 along Florida's northwest coast (Big Bend).[18]
- Hurricane Michael was a deadly Category 5 hurricane with sustained wind speeds of 140 mph that made landfall on October 10, 2018 in the Florida Panhandle region. It became the strongest hurricane ever recorded to make landfall in the Florida Panhandle.[19]
- Hurricane Sally made landfall on September 16, 2020 along the Alabama state line and western Florida Panhandle.[20]

[18] (Berg, Robbie 2017).

[19] (Beven et al. 2019, National Weather Service (NWS) 2020).

[20] (National Weather Service (NWS) 2020).

These extreme hurricanes caused widespread and significant damage to the Florida Panhandle region and carved a path of destruction that left thousands of people without power. As such, this chapter focuses on sixteen counties in Northwest Florida: Bay, Calhoun, Escambia, Franklin, Gadsden, Gulf, Holmes, Jackson, Jefferson, Leon, Liberty, Okaloosa, Santa Rosa, Wakulla, Walton, and Washington. Figure 6.1 depicts the study area.

Data description

Different data sets were employed, including spatial information on demographics, lodging establishments, shelters, and the regional roadway network.

The demographic data including census block groups were acquired from the 2014-2018 American Community Survey (ACS) Census estimates.[21] There are 872 census block groups in Northwest Florida with a total population of 1,448,054 people. Figure 6.2a shows the total population of each block group in the study area.

[21] (US Census Bureau 2020b).

The data related to the lodging establishments (i.e., hotels, motels, bed and breakfasts, resort condominiums, and resort dwellings) were downloaded from the Florida Geographical Data Library (FGDL),[22] based on the Florida Department of Business and

[22] (Florida Geographical Data Library (FGDL) 2017).

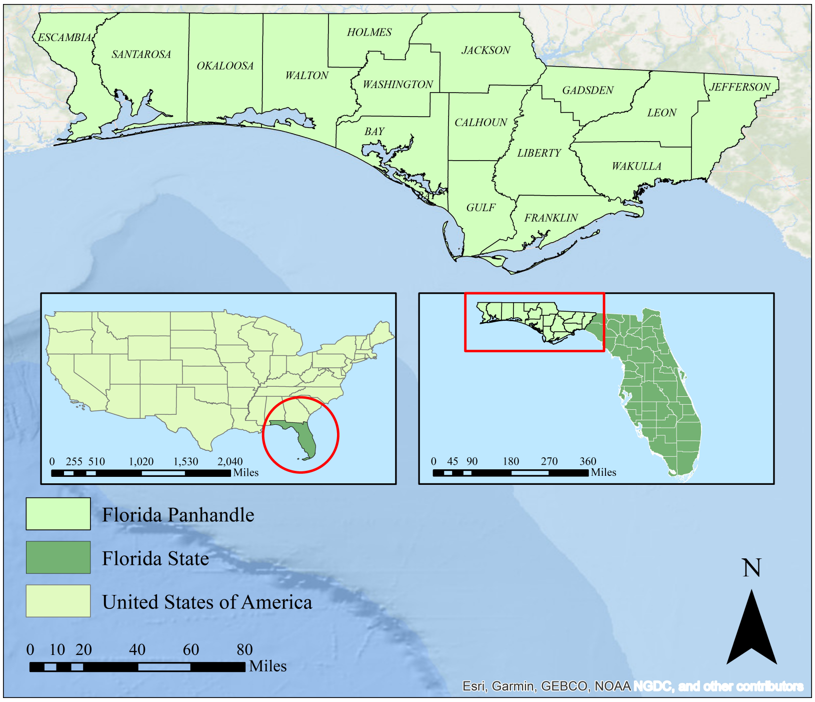


Figure 6.1: Location of the study area

Professional Regulation (DBPR).

The shelter data set was obtained from the National Shelter System Facilities.[23] These data sets indicate that there are 247 and 1725 congregate and non-congregate shelters in the study area, respectively. Figure 6.2b and Figure 6.2c illustrate the spatial distribution of these facilities in Northwest Florida. As seen, there are many lodging establishments located in coastal areas, as many of these places attract tourists. Also, there are many facilities as well as congregate shelters around the City of Tallahassee.

[23] (Homeland Infrastructure Foundation-Level Data (HIFLD). 2018).

The roadway network data was obtained from the Florida Standard Urban Transportation Model Structure (FSUTMS)[24] The roadway network is shown in Figure 6.2d.

[24] (Florida Standard Urban Transportation Model Structure (FSUTMS) 2018).

Access to shelters

This section presents our methodology employed to measure the spatial access of people in Northwest Florida to congregate and non-congregate shelters using both the closest facility and the 2SFCA methods. In order to implement these approaches, travel times on each roadway link were obtained based on the FSUTMS

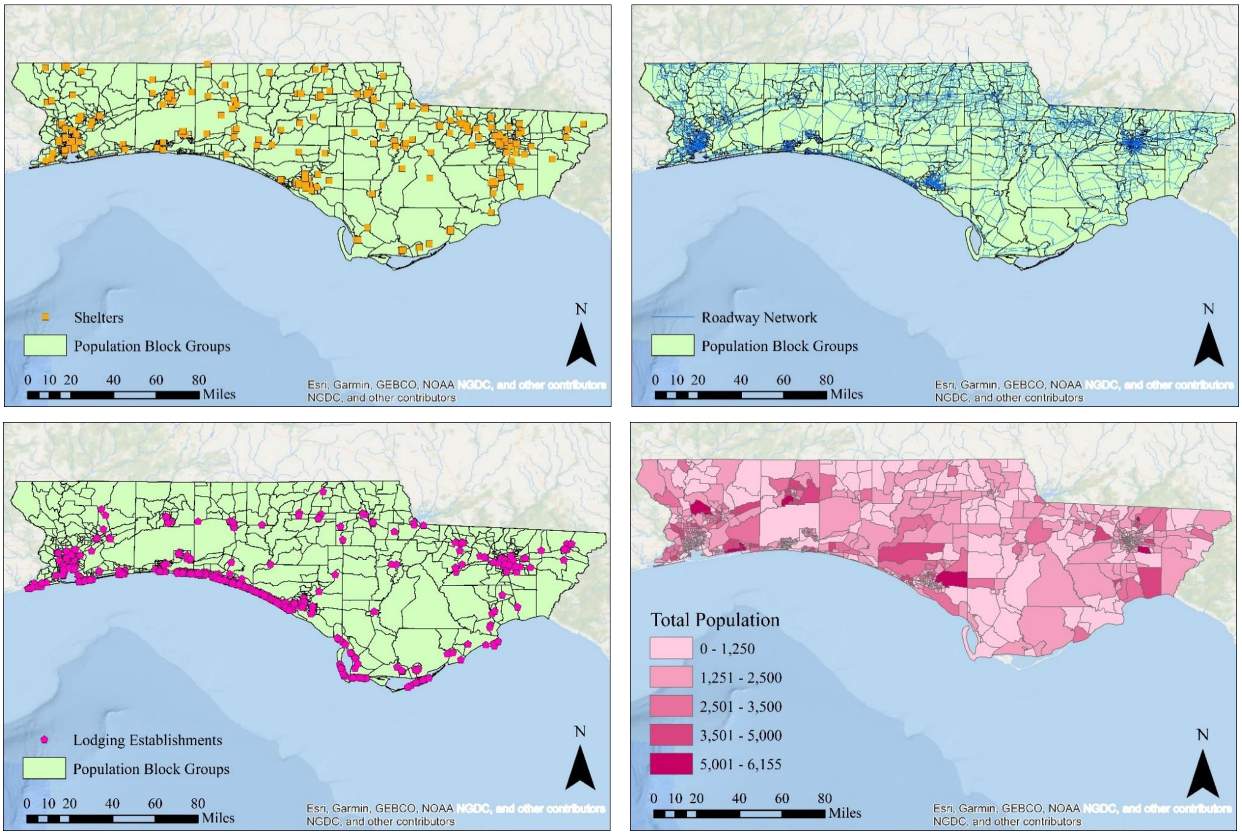


Figure 6.2: Spatial distribution of (a, upper left) total population, (b, upper right) lodging establishments, (c, lower left) shelters, and (d, lower right) roadway network

model built-in CUBE software. It is worth mentioning that the congested travel times on the roadways were considered in the access models. Next, the census block group polygons were converted into geometric centroids. Then, the Network Analyst module (Closest Facility) in ArcGIS software was utilized to calculate travel times to the nearest facility using the optimal or shortest path between the origins and destinations. Origins and destinations here are defined as census block groups' centroids and congregate and non-congregate shelters, respectively. Based on the obtained travel times, the access of census block groups to facilities was visualized using Geographic Information Systems (GIS)-based techniques. The results of the closest facility analysis are illustrated in Figure 6.4a and Figure 6.4b.

Two-step floating catchment area

The 2SFCA method was applied to identify the census block groups with a high and low level of access to the facilities of interest (congregate and non-congregate shelters) in Northwest Florida. The total population in each block group alone and the capacity of each facility were considered respectively as demand and supply in the methodology. The basic 2SFCA method has two steps.

First, all populations within the facility's j catchment are identified. That is, the provider-to-population ratio is calculated by dividing the capacity of each facility by the total population within the catchment j (Equation 6.1).

The second step identifies all the facilities of a population location within the catchment size. This is obtained by summing up all provider-to-population ratios in the first step. The access index (A_i) is calculated as follows (Equation 6.2):

$$R_j = \frac{S_j}{\sum_{k \in (d_{kj} \leq d_0)} P_k} \tag{6.1}$$

$$A_i = \sum_{j \in (d_{ij} \leq d_0)} R_j \tag{6.2}$$

where (R_j) is the provider-to-population ratio of any facility j, (S_j) is the capacity of facility at location j, (P_k) is the number of total populations within the catchment size, (d_0) is the catchment size, and (d_{kj}) is the travel time from k to j. Two additional metrics, access Index (AI) and access Ratio Difference (ARD), were defined in order to compare the spatial access of each census block group to the facilities obtained via the proposed approaches. The AI was developed to compare the access of census block groups to lodging establishments (non-congregate shelters) and shelters given the corresponding travel times (Equation 6.3). The ARD metric was also defined to compare the access level of each census block group to the facilities obtained by the 2SFCA method. ARD is obtained via subtracting the normalized values of the access ratio for each census block group to non-congregate shelters from congregate shelters (Equation 6.4).

AI and ARD are defined as follows:

$$AI_i = C_{ij,non-congregate} - C_{ij,congregate} \tag{6.3}$$

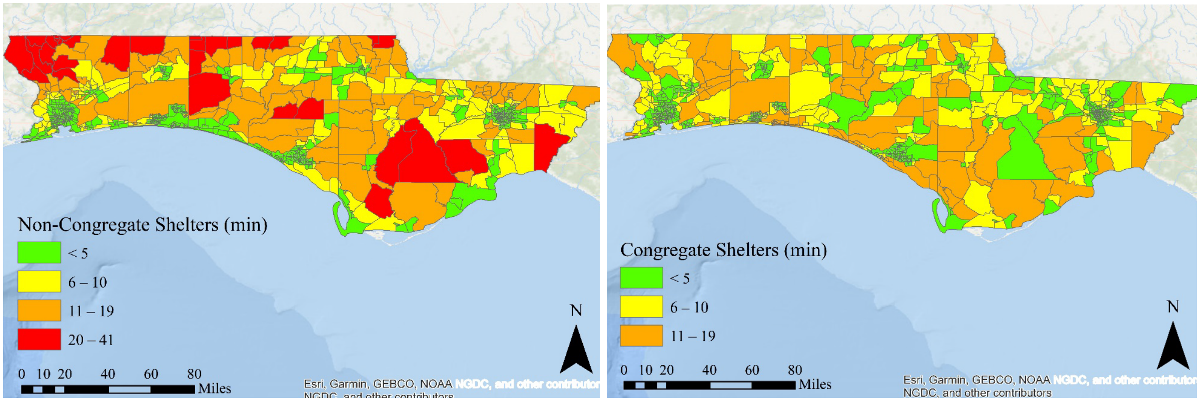


Figure 6.3: Closest facility for (a, left) non-congregate shelters; (b, right) congregate shelters

$$ARD_i = \frac{A_{i,non-congregate}}{\max A_{non-congregate}} - \frac{A_{i,congregate}}{\max A_{congregate}} \tag{6.4}$$

where $C_{ij,non-congregate}$ and $C_{ij,congregate}$ are the travel times for census block group i to non-congregate and congregate shelters, respectively. $A_{non-congregate}$ and $A_{congregate}$ are respectively the access of census block group at location i to non-congregate and congregate shelters. Effectively these measures look at the difference between the two measures for a given census block group i. The AI and ARD metrics results are shown in Figure 6.5.

Findings

In this section, the results of computing people's spatial access to non-congregate and congregate shelters obtained by the closest facility approach are presented in Figure 6.3a and Figure 6.3b, respectively. As seen in Figure 6.3a, the census block groups mainly located in coastal areas have the lowest travel times to non-congregate shelters given the high number of lodging facilities in those regions (Figure 6.2b). There are some census block groups that have lower access to these facilities with respect to travel times more than 20 minutes. These areas are mostly considered as rural areas in Northwest Florida. In contrast to non-congregate shelters, coastal areas have lower access to congregate shelters with regard to their higher travel times (Figure 6.3b).

A comparison between the access to the facilities revealed that the maximum travel time to access to congregate shelters is less than non-congregate shelters in Northwest Florida. However, as previously mentioned, there is a higher number of lodging

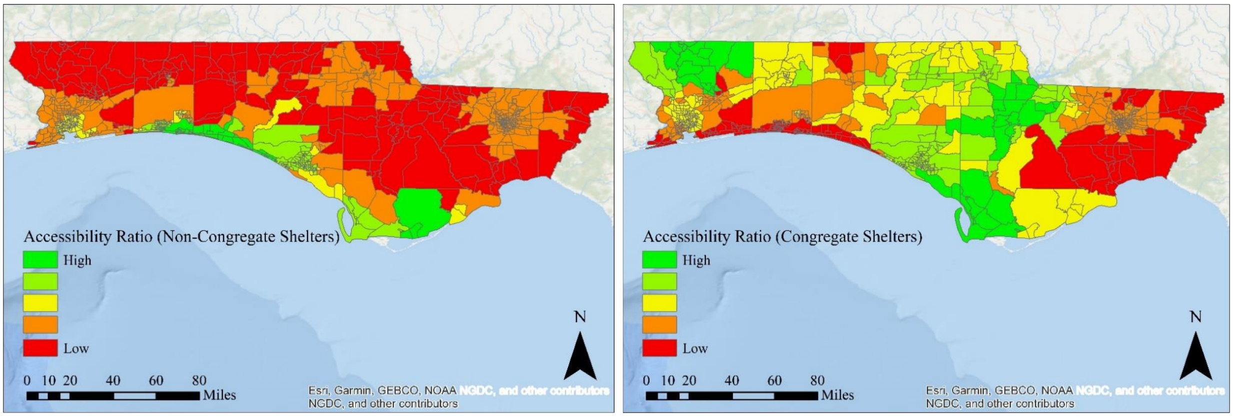


Figure 6.4: Results of the 2SFCA method for (a, left) non-congregate shelters; (b, right) congregate shelters

establishments than shelters in the study area. Another interesting finding is that the City of Tallahassee was highly accessible to both types of facilities (less than 5 minutes) based on the high number of facilities located in the city. Considering the capacity of facilities, the 2SFCA method revealed a different pattern compared to the previous findings regarding the access to non-congregate shelters. As seen in Figure 6.4a, most of the census block groups in Northwest Florida have low access to non-congregate shelters given the computed ratios. The ratio of lodging establishments' capacities to total population is very low in those regions. It can be concluded that non-congregate shelters in Northwest Florida cannot fully satisfy the demands of the population if we use those facilities as shelters. However, similar to the results obtained by the closest facility approach, the coastal areas mostly have a high level of access to non-congregate shelters, which is shown by the green color. In terms of access to congregate shelters, the findings indicate that several census block groups have high access ratios (Figure 6.4b). That is, the residents of these areas have high access to these facilities. The City of Tallahassee also reveals a different pattern and has low access to the facilities given the low computed access ratios.

The obtained results of AI and ARD metrics are shown in Figure 6.5a and Figure 6.5b, respectively. It is important to note that in Figure 6.5a, the green color shows higher spatial access for each census block group to non-congregate shelters compared to congregate shelters. In Figure 6.5b, the red and orange colors indicate higher access to congregate shelters than non-congregate

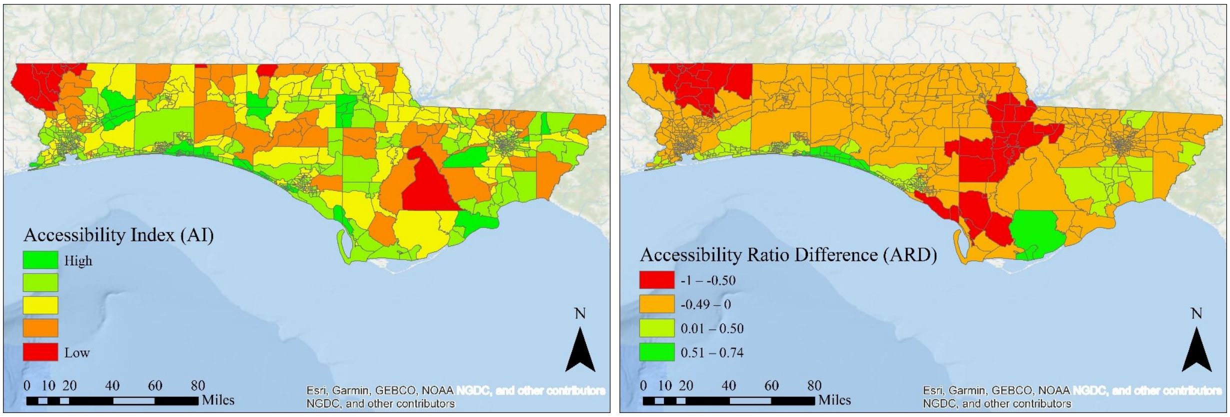


Figure 6.5: Results of the (a, left) access index (AI); (b, right) access ratio difference (ARD)

shelters. As seen, census block groups mainly located in coastal areas have better access to non-congregate shelters. According to the obtained results by the ARD metric, most of the census block groups have negative values (shown in red and orange). It can be concluded that most of the census block groups in Northwest Florida have higher access to congregate shelters compared to non-congregate shelters given the capacity of these facilities. Although there are many lodging establishments in Northwest Florida, the findings show an imbalance between the supply and demand in these regions. Hence, this might cause serious challenges for the residents of these areas to use non-congregate shelters for evacuations and sheltering during the hurricane season with the COVID-19 pandemic present. As stated previously, many of lodging establishments are clustered in coastal areas since these facilities attract tourists. According to the findings, the residents who live in coastal areas could benefit from lodging facilities to address the congregate shelters capacity shortage despite a lack of these facilities. Also, it is imperative to note that many of census block groups with lower access to non-congregate shelters appear to be in rural areas. In contrast to census block groups located in coastal areas, people who live in other regions might have critical problems in terms of using lodging facilities due to a lack of enough capacity.

Conclusions

This chapter assessed the spatial access of US census block groups in Northwest Florida to non-congregate and congregate shelters through the closest facility and 2SFCA methods. Two metrics of access Index (AI) and access Ratio Difference (ARD), were developed to compare the access of each census block group to the facilities.

The findings of the access analysis showed that non-congregate shelters are not equally distributed in Northwest Florida. Results revealed that census block groups located in coastal areas have better access to non-congregate shelters due to a higher number of lodging facilities clustered in these regions. However, considering the capacity of each facility, many areas in Northwest Florida have lower access to non-congregate shelters compared to congregate shelters.

Lodging facilities cannot fully satisfy the demands of the total population in the case of non-congregate sheltering during a global pandemic such as COVID-19.

Most of the census block groups with lower access to non-congregate shelters are rural areas. Furthermore, the City of Tallahassee, the capital of Florida, located in Leon County, has high access to both non-congregate and congregate shelters given the obtained travel times via the closest facility. However, the 2SFCA method findings indicated a different pattern for Tallahassee given the low spatial access ratio.

Next

The findings of this chapter provide a better picture regarding the spatial access to the facilities in Florida Panhandle which can provide valuable information for state officials and decision-makers to identify the areas with low access to the facilities and highlight those regions for future improvements.

The knowledge obtained from this chapter has the potential to raise the awareness of planners to provide further access to non-congregate shelters for vulnerable areas. This might be obtained by establishing new facilities and especially lodging establishments in those regions to prevent a potential shortage. In addition, allocating additional shelter space can increase the shelters' capacity to safely practice social distancing measures and

to prevent the spread of the disease. In addition, it is also possible that regular congregate shelters can be re-purposed as pandemic shelters. The identification of which shelters to re-purpose is an interesting research direction to pursue. In the case of such an uncontrolled outbreak, non-congregate sheltering could save evacuees from exposure to COVID-19 and practice social distancing recommended by the CDC, specifically during the hurricane season.

Variable catchment sizes could be used for the 2SFCA to enhance the efficiency of this method. Furthermore, in this chapter, we focused only on the total population who live in a census block group in Northwest Florida. However, considering the aging population (65+) that are at a higher risk of getting infected with COVID-19 and consist of a substantial percentage of people in Florida could be a valuable extension for future work.

Measuring the spatial access to non-congregate and congregate shelters given different transport modes such as public transit, private car, biking, walking, can be another interesting future research direction, particularly as networks may become disrupted due to the event people aim to evacuate from.[25] Finally, assessing the disparities in spatial access due to different income levels, races, and ethnic groups would be an interesting potential future research.

[25] (Cui and Levinson 2018a).

7
Access and Centrality-Based Estimation of Urban Pedestrian Activity

Brendan Murphy, Andrew Owen, and David Levinson

Abstract: This chapter predicts pedestrian activity at 1,123 intersections in Minneapolis, Minnesota, using scalable and transferable predictive variables such as economic access by sector, betweenness network centrality, and automobile traffic levels. Access to jobs by walking and transit, automobile traffic, and access to certain economic job categories (Education, Finance) were found to be significant predictors of increased pedestrian traffic, while access to other economic job categories (Management, Utilities) were found to be significant predictors of decreased pedestrian traffic. Betweenness centrality was not found to be a significant predictor of pedestrian traffic. Access-based analysis may provide city planners and engineers with an additional tool to predict pedestrian and bicycle traffic where counts may be difficult to obtain, or otherwise unavailable.

Introduction

Keywords: Pedestrian travel; Access; Travel demand; Active transport

Walking and bicycling are increasingly becoming important transport modes in modern cities for a multitude of reasons, including individual and societal wellness, environmental externalities associated with motorized modes, and resource availability. Planning for biking and walking, and creating societal programs to increase their levels, has been cited as a targeted health need in urban planning going forward.[1] In addressing the viability

[1] (Brownstone 2008, Ermagun and Samimi 2018, Raford and Ragland 2004).

and availability of alternative modes, high-resolution spatial data on non-motorized transport behavior patterns is needed.

Rates of walking and bicycling to work in the United States hover around 2.8% and 0.6%, respectively, with public transit use barely higher at 5% nationally.[2] Proper placement of pedestrian treatments and improvements has implications to both safety[3] and access and mode choice,[4] but information regarding estimated non-motorized traffic levels is needed to locate areas in need of improvement. In determining salient locations for non-motorized improvements, it is important to have accurate records of both current and potential travel demand (e.g., current levels of walking in a neighborhood, as well as good models of increased demand due to potential treatments); however good quality, high-granularity data sets for non-motorized travel can be difficult to obtain, especially standardized for national spatial inventories.[5] For this reason, practitioners and researchers must frequently rely on estimation models for non-motorized traffic, and various methods can suffer from issues of data quality, granularity, and the presence of location-specific variables.[6]

[2] (McKenzie et al. 2014).

[3] (Schneider et al. 2004).

[4] (Iacono et al. 2010).

[5] (McDaniel et al. 2014).

[6] (Carlson et al. 2019).

Many of the issues with the collection of standardized non-motorized transport data have to do with the factors that influence pedestrian and bicycle behavior. A model of active transport risk assessment is uninformative if the pedestrian and vehicular flows do not accurately represent corresponding levels *in situ*, and many cities do not have dense data sets of active transport flow levels, instead favoring counts of vehicle traffic. As such, active transport flow levels must be extrapolated from sparse data sets using comprehensive methodologies.

Land use data are well-documented by the US Census Bureau to the Census Block level of resolution, and general socioeconomic characteristics are maintained as well, and can have significant influence.[7] However, more specific socioeconomic characteristics are salient in non-motorized travel beyond just adjusted income levels, as well as weather variables[8] and latent, subjective variables such as visibility and perceptions of lighting, which can be more difficult to obtain at high spatial resolution, and can complicate inter-city comparisons. For these reasons, as well as the overall lack in non-motorized travel counts for many communities, methods of estimating pedestrian and bicycle behavior that do not rely heavily on high-resolution count data area applied in this chapter.

[7] (Ermagun and Samimi 2018, Schneider et al. 2010).

[8] (Ermagun et al. 2018).

Aggregate travel behavior studies typically involve analysis at the level of Transport Analysis Zones (TAZs), which are too coarse to allow robust analysis of non-motorized travel.[9] Regional travel surveys consider many trip purposes, but are similarly coarse, and typically have sample sizes too small to allow for robust city-to-city comparison. Census block-level information regarding economic access (access to jobs) via both strictly walking, and via the net access benefit of public transport, will first be used to explain observed pedestrian traffic at a subset of intersections in the city of Minneapolis, Minnesota. Road network betweenness centrality will also be used as an explanatory variable, as a proxy of the underlying network structure. A framework for comprehensive pedestrian risk assessment modeling, using pedestrian volume, vehicle volume, and an environmental factor (crosswalk length) on a university campus has also been constructed.[10] The motivation for constructing models of pedestrian and vehicular traffic is in supplementing the sparse data currently available, and deriving a reusable framework to provide a more complete picture of pedestrian activity throughout the city at the level of individual intersections, based on non-location-specific available data.

[9] (Biehl et al. 2018, Iacono et al. 2010).

[10] (Schneider et al. 2004).

Questions

This chapter addresses the following question:

- What factors predict the number of pedestrians?

We use betweenness, access, and traffic levels to estimate a regression model to predict pedestrian flows at intersections in Minneapolis.

Methods

Data

This section briefly describes the data sources used in the pedestrian estimation models, and the data preparation process.

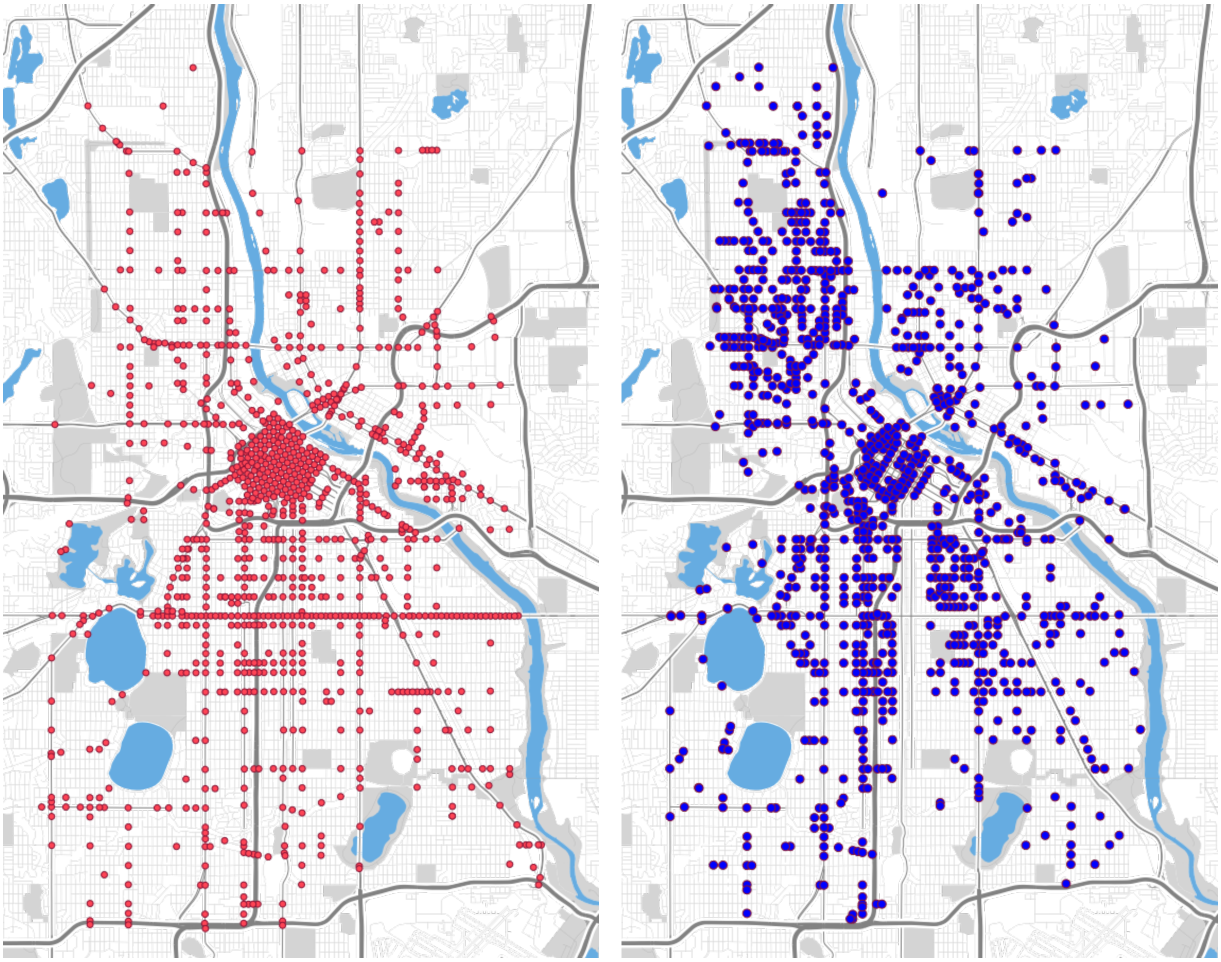
- **Data Sources**

  1. US Census TIGER 2010 data sets: blocks, core-based statistical area (CBSA) for Minneapolis-St. Paul.

2. US Census Longitudinal Employer-Household Dynamics (LEHD) 2011 Origin-Destination Employment Statistics (LODES).
3. OpenStreetMap (OSM) North America extract, retrieved April 2014.
4. Turning movement counts (TMC) 2000-2013, City of Minneapolis.
5. Average Annual Daily Traffic (AADT) measurements 2000-2013, City of Minneapolis.
6. GTFS data from Metro Transit.

- **Data Preparation**
  1. Construct pedestrian travel network graph for Minneapolis.
  2. Geocode pedestrian Turning Movement Count (TMC) and Average Annual Daily Traffic (AADT) data to spatial locations.
- **Access and Centrality Calculation**
  1. For each Census block in Minneapolis, calculate travel time to all other blocks within a 5km radius for a single departure time
  2. Calculate cumulative opportunity access to jobs for each census block, using travel-time thresholds of 5, 10, 15, 20, 25, and 30 minutes.
  3. Calculate net transit access benefit using a threshold of 30 minutes.
  4. Calculate betweenness centrality for the Minneapolis OSM road network.
- **Model estimation**
  1. Construct linear regression of pedestrian behavior on walking access, net transit access, network centrality, and access to job opportunities by sector.
  2. Assess and validate model on sample of other intersections in Minneapolis.

Intersection locations were determined from OSM road centerline data for the Minneapolis-St. Paul CBSA (Core-Based Statistical Area). The subset of intersections for which count data were available is displayed in Figure 7.1a; these intersections were used to construct the predictive models. Access calculations were



(a) Raw pedestrian count data

(b) Intersections used in estimated pedestrian activity analysis

Figure 7.1: Location of intersections in Minneapolis

performed using OpenTripPlanner (OTP) open-source routing software; GIS work performed in QGIS and PostGIS; network centrality measures computed in ArcMap GIS with the Urban Network Analysis Tools toolbox; statistical work done in SQL, Python, and R. Figure 7.1b displays the locations of intersections in Minneapolis used to estimate pedestrian activity and validate the model.

Access

The first type of explanatory variable used in the model of Minneapolis pedestrian count data is cumulative opportunity measure.[11] Using OTP, walking travel times along the network are calculated from each Census block centroid in Minneapolis, to each other block centroid within the travel-time thresholds of 5, 10, 15, 20, 25, and 30 minutes. Job opportunities are summed from each block centroid reachable within a given time threshold, yielding an X-minute access measure. Job opportunities are broken down by economic sector, as defined by the North American Industry Classification System. There are two access calculations used in this chapter:

[11] See chapter 1 in this volume.

1. Access to jobs from Census block centroids by walking
2. Access to jobs from Census block centroids by transit and walking

Pedestrian counts are often taken at intersections in either gross counts, or divided by turning movement type. This chapter uses Turning Movement Count (TMC) data from approximately 750 intersections in Minneapolis; intersection counts were calculated by adding the various TMC types for each intersection in the analysis group, to yield a gross figure of pedestrian activity within an intersection. Two-hour counts for pedestrian activity were used for morning peak (7:00 - 9:00 AM), midday (11:00 AM - 1:00 PM), and afternoon peak (4:00 - 6:00 PM).

We predict that origins exhibiting higher access values would see greater pedestrian activity throughout the day. Access for both walking, and walking + transit modes, are used in the estimation models; subtracting walking access from the multimodal walking + transit access yields the net transit benefit, and including walking and net transit separately in the regression models allows for explicit evaluation of how important transit benefits are to influencing pedestrian activity. Multiple regression in the *R* statistical package was then performed to determine the explanatory power of the access measures in predicting pedestrian and vehicular traffic in the morning, midday, and afternoon peaks, as well as for a 6-hour summed count. These additional tables are omitted here. It was expected that origins exhibiting higher walking-access values, and higher centrality values, would see greater pedestrian activity throughout the day.

Centrality

In an attempt to reflect pedestrian activity on the underlying topology of the transport network, a centrality measure was computed in ArcGIS with the Urban Network Analysis Toolbox, and added to the regression models. Various types of network measures of centrality have been proposed in their applicability to estimation of non-motorized activity levels,[12] and safety and collision rates.[13] One of the most common measures of centrality is "betweenness" centrality, or how "between" other nodes or links a given node or link is. When considering route choice and estimating modal traffic flows, link betweenness centrality is often considered, and consists of the proportion of shortest paths between all node pairs that pass through a link or node.[14] Relatedly, stress centrality consists of counting the number of times each link in a given network is utilized among the set of shortest paths between all node pairs, and is given by:

[12] (Anciães 2011, Do et al. 2013, McDaniel et al. 2014).

[13] (Dai et al. 2010, Zhang et al. 2015).

[14] (McCahill and Garrick 2008).

$$C_s(k) = \sum_{i,j \in V} \sigma_{ij}(k) \qquad (7.1)$$

where σ_{ij} is either 1 if link k is used in shortest path σ_{ij}, and 0 otherwise. This form of stress centrality has been used to spatially assess transport systems.[15] In order to adapt stress centrality to the specific characteristics of non-motorized travel, the following modifications to the link betweenness schematics for the bicycle mode have been made:

[15] (Derrible 2012).

1. Restrict shortest paths to preferred bicycle routes
2. Restrict origin-destination (O/D) pairs to only locations reachable by bicycle
3. Modify O/D frequency with trip multipliers[16]

[16] (McDaniel et al. 2014).

However, for walking, it is not reasonable to include the entire set of road network intersections as possible destinations for a given intersection-origin, due to the lower speed of walking – an assumed 5 km/h. Thus, for the centrality calculations for the walking mode, an on-network radius of 5 km, to represent an hour of walking at average speed, was implemented to increase the saliency and relevance of centrality to actual walking.[17]

[17] Additionally, similar modifications to the above for bicycle modes may be implemented for walking, in particular modifying O/D frequency to reflect that a certain subset of nodal origins and destinations exhibit much higher activity levels than others; for simplicity, such modifications were not attempted in this chapter.

Stress centrality is first used to evaluate preliminary explanatory power, and feasibility of applying centrality metrics to this model.

To reflect typical work trips, McDaniel et al.[18] chose O/D pairs such that origins were strictly residential parcels, and non-residential parcels were destinations in the morning, and the order was reversed in the afternoon. However, the authors speculated that allowing for non-residential destinations in the afternoon to reflect more complex after-work tours could increase model explanatory power. Additionally, O/D pairs were limited by a network distance threshold of 5 miles, per the National Household Travel Survey.[19] O/D multipliers specified relative magnitude of trip generation, since parcels are heterogeneous in their trip generation capacity; these included density of dwelling units within residential parcels, and square footage density for all other parcels. These modifications constitute potentially salient areas for further investigation in our model of pedestrian traffic. O/D pairs can be tailored to favor walking trips from residential parcels to commercial destinations, as well as limited to reasonable walking distances attained within a 30-minute threshold (2.5 km).

[18] (McDaniel et al. 2014).

[19] (US Department of Transportation 2009).

Pedestrian activity estimation

Multiple regression over the explanatory variables was performed in *R* for the walking mode. Different time-thresholds of access were compared for explanatory power of pedestrian activity, of which the strongest threshold was chosen for a final parsimonious model to estimate pedestrian traffic throughout the sampled intersections. Iterative stepwise regression was performed using the economic sector access variables, in an attempt to account for the possible differential walking trip generation levels of different job sectors. The parsimonious model is then applied to a broader sample of intersections within Minneapolis, and the estimated pedestrian levels are compared to actual counts for validation, and specific spatial areas of underestimation and overestimation are discussed.

Findings

Full tabulation of all bivariate regression models, to determine which time thresholds and peak-hour periods to use for greatest explanatory power in modeling pedestrian traffic levels, are omitted for brevity. It was found that the 15-minute threshold of total access, combined with the afternoon-peak period pedestrian counts and other variables, yielded the best explanatory power for walking

Table 7.1: Summary statistics

Description	μ	σ
Intersection total ped activity per day	633.66	2023.20
Intersection morning ped activity per day	194.70	570.34
Intersection midday ped activity per day	270.74	994.79
Intersection afternoon ped activity per day	264.52	733.49
Intersections with afternoon ped counts	741	
Intersections included in model	1123	

Note: Summary statistics for data sets used in pedestrian activity analysis: pedestrian turning movements between 2000 and 2013 for the City of Minneapolis.

access. A parsimonious model for walking activity, in terms of the strongest explanatory variables, is reported in Table 7.2. Net transit access benefit was included as an explanatory variable in the pedestrian activity estimation model, to account for the effect of transit in urban cores of increasing pedestrian activity by attracting additional users beyond pure foot traffic. Table 7.1 lists summary statistics for the data sets used in the following analysis: automobile-pedestrian crashes between 2000 and 2013, and pedestrian turning movement counts between 2000 and 2013 for Minneapolis.

First, the pedestrian counts were modeled in terms of only walking access, for different thresholds and times of day. From this, the strongest explanatory power was determined for afternoon peak period counts, at a 15-minute access threshold. Pedestrian counts were then modeled in terms of transit and walking access (bimodal access), for different times of day. A 30-minute transit threshold was used, in accordance with the reported data available in the *Access Across America: Transit 2014* report.[20] Net transit access, a measure which looks at the contribution to access from transit service, was also investigated as a potential explanatory variable for walking activity. A threshold of 30-minutes was again used. Betweenness centrality was included to relate walking activity to the underlying network structure. Access and betweenness centrality are mapped in Figure 7.2.

[20] (Owen and Levinson 2014).

Access to Education and Finance jobs were found to be significantly predictive of increased pedestrian activity, while access to Management and Utilities jobs were found to be significantly predictive of decreased pedestrian activity, relative to other

Table 7.2: Parsimonious regression model results. Dependent variable: average pm pedestrians

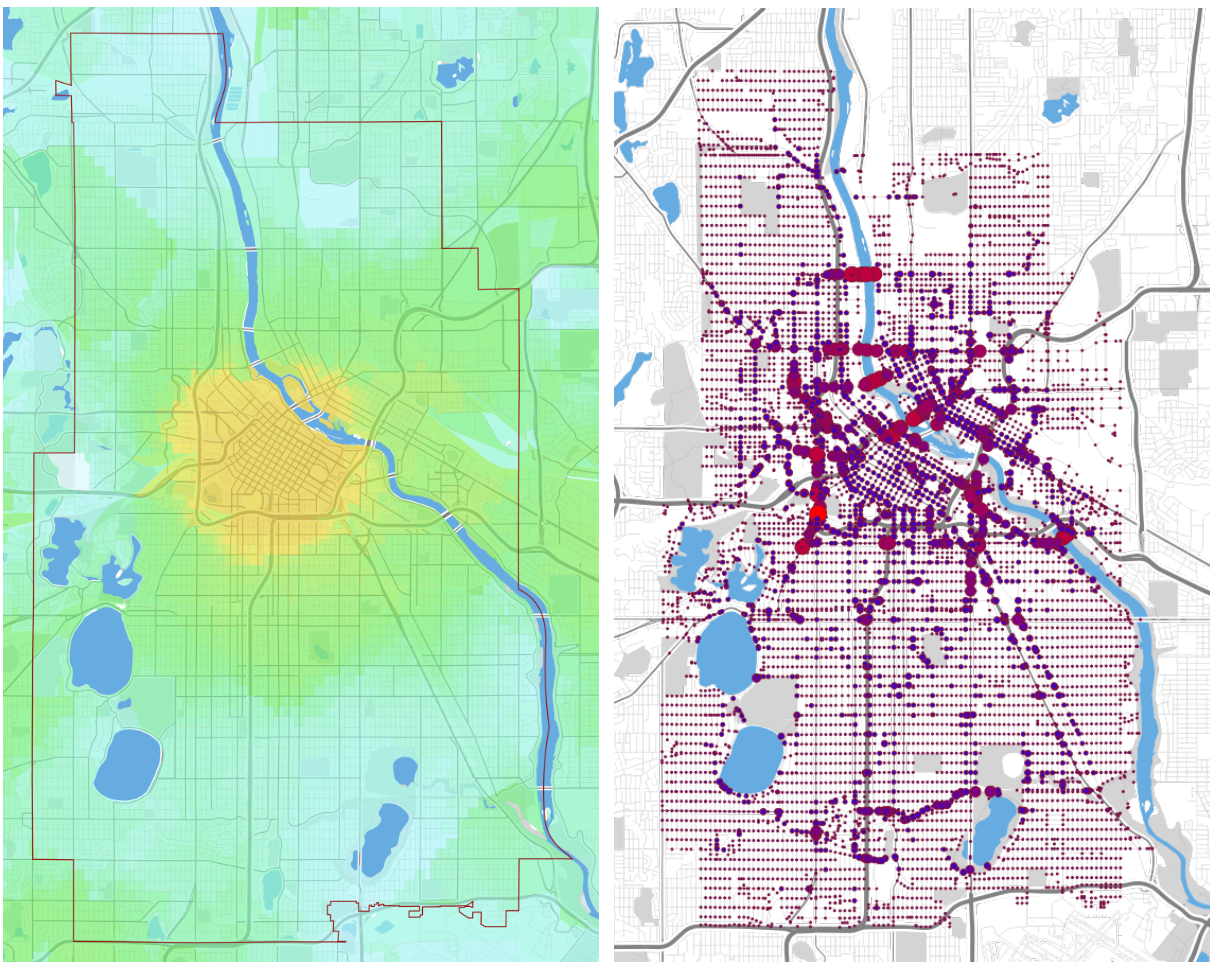
Variable	With AADT		Without AADT	
AADT	1.312	*		
	(0.679)			
Walking access	0.410	**	0.649	***
(15-minute)	(0.173)		(0.112)	
Net transit access	0.320	***	0.129	**
(30-minute)	(0.093)		(0.053)	
Stress betweenness	0.029		0.487	***
	(0.371)		(0.186)	
Management jobs	-0.114	***	-0.109	***
(5-minute)	(0.033)		(0.017)	
Education jobs	0.922	***	0.700	***
(5-minute)	(0.086)		(0.058)	
Finance jobs	0.071	***	0.054	***
(10-minute)	(0.009)		(0.006)	
Utilities jobs	-0.968	***	-0.729	***
(15-minute)	(0.104)		(0.071)	
Constant	-15.208		-1.698	
	(9.874)		(4.795)	
Observations	486		1,016	
R^2	0.287		0.226	
Adjusted R^2	0.275		0.221	
Residual Std. Error	83.830		72.773	
F Statistic	23.970	***	42.139	***

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; (standard error)

categories. Utility jobs tend to be concentrated in areas not immediately in the downtown core, as well as management jobs to a lesser degree; finance jobs are heavily concentrated in the downtown core area, and education jobs are concentrated on walkable campuses. Further, it is plausible that certain categories of jobs attract greater or lesser levels of walking among their workers, dependent on such factors as dress requirements, vehicle needs (e.g. construction and contract workers), and typical density of jobs within each category. Additional cross-comparison analysis among economic job categories is needed to investigate these effects, but initial analysis indicates these spatial distributions correlate to the regression coefficients in Table 7.2.

A series of maps shows additional views of the data used in the modeling process; Figure 7.2a shows access to jobs within 30 minutes by walking in Minneapolis, and Figure 7.2b shows the betweenness centrality of all intersections in Minneapolis calculated with a 5km radius. Access by walking, given the walking mode's uniform nature, shows where economic activity is most concentrated in the region. Centrality gives a sense of the most important nodes in the street network of Minneapolis – that is, the nodes that would affect the highest number of shortest paths, were they to be rendered impassible. Both of these calculations showed positive correlations with pedestrian activity, as shown in Table 7.2. Figure 7.3a shows the raw levels of daily pedestrian activity, aggregated from manual pedestrian counts between 2000 and 2013, while Figure 7.3b shows the estimated levels of afternoon peak pedestrian activity in Minneapolis, calculated using the model definitions outlined in Table 7.2. To validate the estimated model, the difference between actual and estimated pedestrian activity is mapped in Figure 7.4.

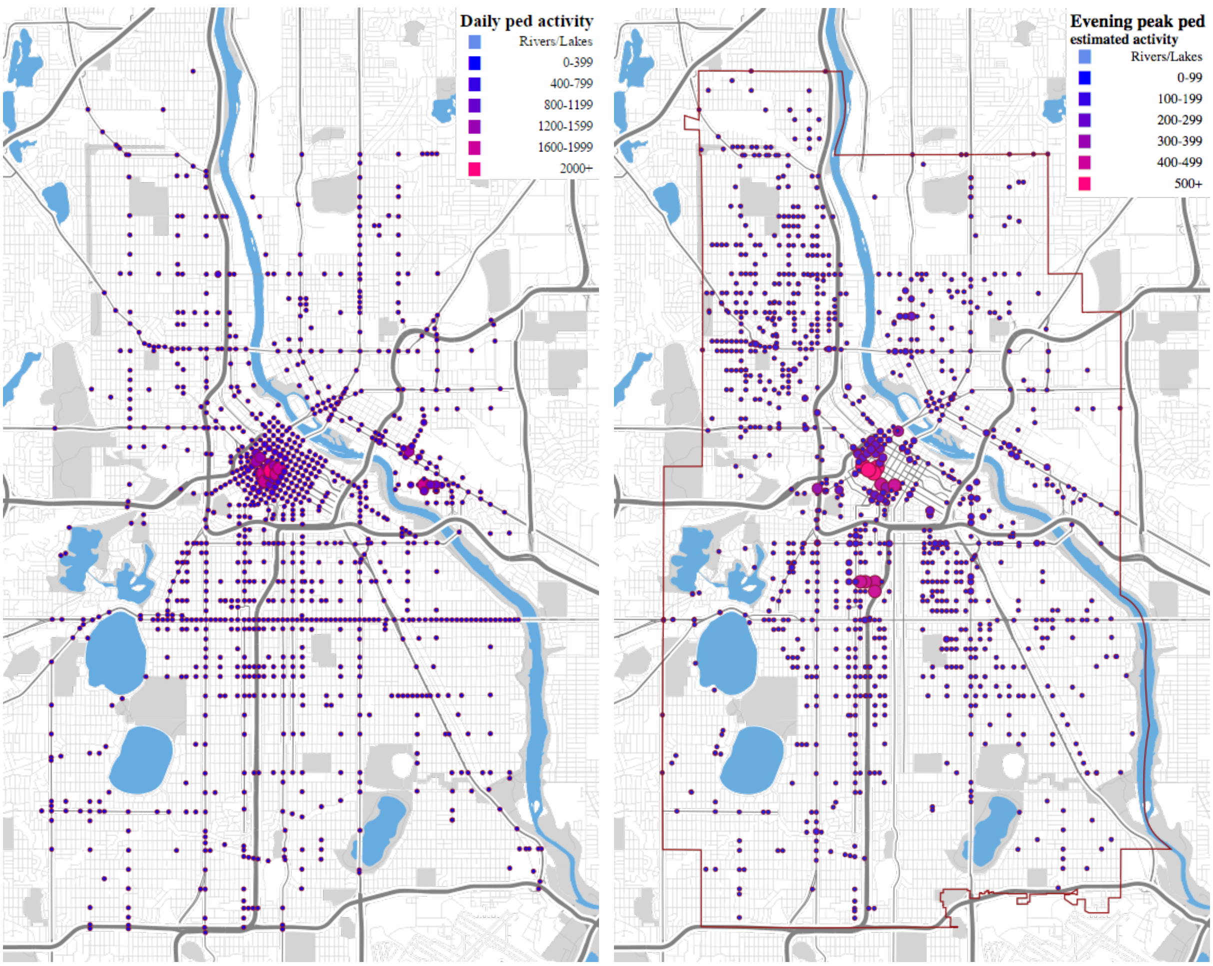
There are a few caveats to mention regarding the ability of simply access and centrality to accurately predict pedestrian behavior. Figure 7.4 highlights sections of the urban area where the model differed significantly from the actual pedestrian counts. For 741 intersections, the number of daily pedestrians was overpredicted, and for 275 intersections the model underpredicted pedestrian activity. The distribution of differences has a mean $\mu = -8.10$ and standard deviation $\sigma = 72.50$; 91.11% of the sampled intersections had $actual - estimated$ differences within 1 standard deviation from the mean. The cases of underestimation and overestimation are geographically interesting to note; the two major areas of underestimation are the inner downtown core, and the East Bank Campus of the University of Minnesota, just east of the Mississippi River, while the major area of overestimation is located west of Hennepin Ave in downtown, near Dunwoody Boulevard and Olson Memorial Highway. The downtown core and the campus of the University are characterized by significant pedestrian activity and are considered walkable areas, whereas the areas just west of downtown are not as walkable; in fact, Dunwoody Boulevard, Olson Memorial Highway, and other roads in the area are multi-lane automobile thoroughfares. While the road network structure and proximity to downtown would predict significant pedestrian activity, physical barriers exist within the built environment. These



(a) Access to jobs within 30 minutes by walking

(b) Betweenness centrality of all intersections; radius of 5km

Figure 7.2: Minneapolis access and betweenness centrality



(a) Raw levels of daily pedestrian activity, 2000-2013 (b) Estimated levels of afternoon peak pedestrian activity.

Figure 7.3: Minneapolis raw and estimated afternoon peak pedestrian activity

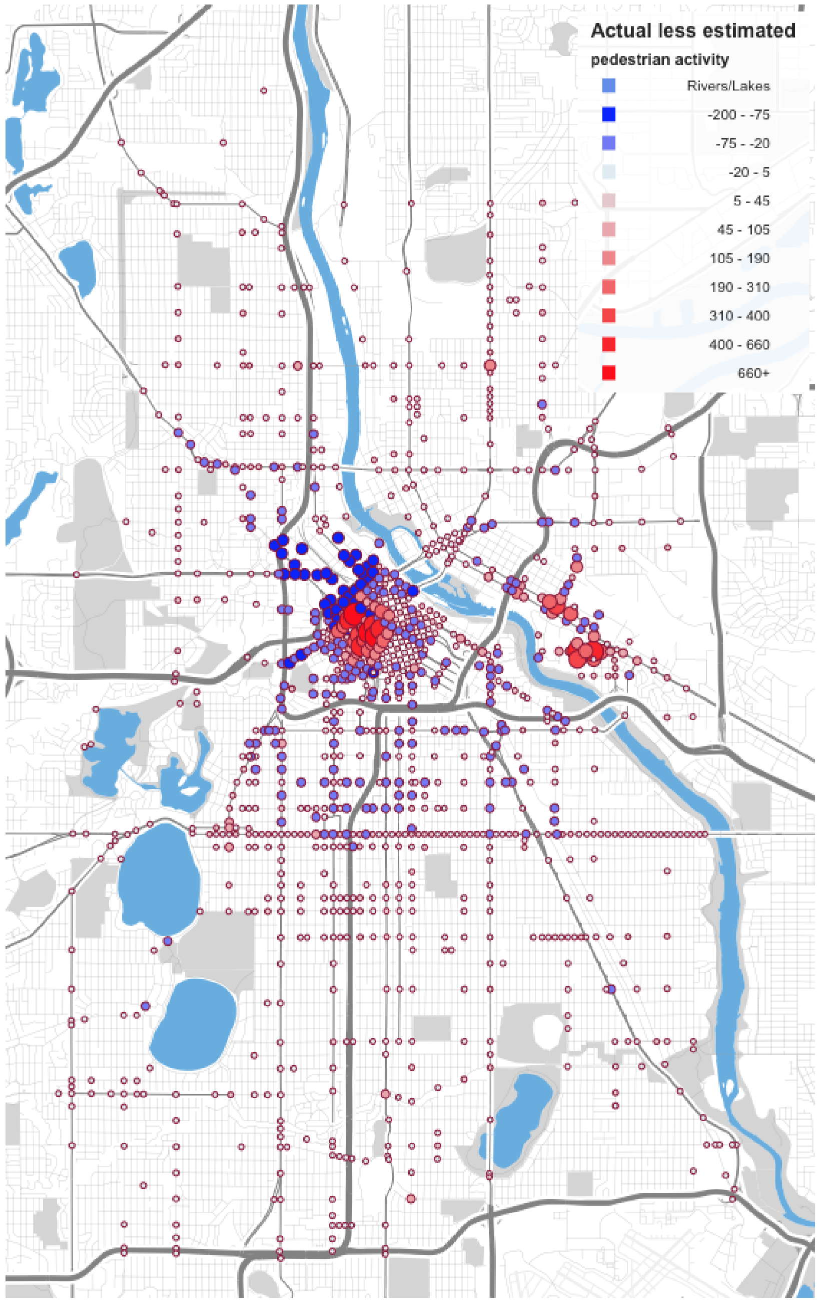


Figure 7.4: Actual minus estimated pedestrian activity, afternoon peak period. Reds are areas of underestimation; blues are areas of overestimation.

cases highlight the limitations of centrality and access in capturing elements of the built environment relevant to pedestrian activity where local and hyper-local factors may play significant roles.

Conclusions

For the bivariate models of pedestrian activity in terms of census block centroid access to jobs via walking, the afternoon peak period provided the best explanatory power. For all three time periods, as well as the 6-hour total count, R^2 values peaked near 15-minute thresholds, and dropped off in either direction. The correlation between walking access and walking activity is positive. Walking is commonly thought of as a 15-minute-mode, in that the majority of people walking in urban areas will be on trips of duration 15 minutes or less. Further, in dense urban areas, distance matters – a high-threshold measurement of walking access will tend to blur the results and differences between origin points, thus potentially failing to reflect local variabilities in walking patterns. Additionally, access data at the 5-minute threshold level was found to be a consistently less significant predictor of pedestrian activity than higher thresholds.

It was found that pedestrian counts in the afternoons exhibited the strongest correlations with the access variables tested, and midday counts exhibited the weakest correlation strengths. It is possible that midday pedestrian traffic is more dispersed in both nature of trip-making and timing, due to variable work schedules. Both the morning and afternoon periods exhibited stronger correlations with job-based access metrics, in accordance with traditional work commute timings. The subtle difference between the two periods could be explained in part through analysis of individual trip diaries – specifically the distributions of departure and arrival times for morning and afternoon trips.

As was hypothesized, both the access measures and betweenness centrality exhibited positive influences on pedestrian activity levels, with all the significant variables with strongest R^2 metrics having positive signs. This gives a reasonable framework through which to estimate modal traffic levels at every intersection in Minneapolis and, by extension of the broader framework, in other cities as well. However, betweenness centrality did not exhibit as strong a positive correlation as was predicted. this may have resulted from the specific methodology used – that is, a centrality calculation that

takes into account heterogeneous trip generation within an urban area due to varying land use patterns may lead to higher predictive power of centrality measures toward actual pedestrian behavior patterns. Pedestrian behavior in urban areas does not exhibit uniform all-to-all trip generation distribution; rather, there are major sources and attractors, which would shift the distribution of route choices, and thus link and intersection centrality, to favor routes between those origin-destination pairs.

Next

A significant and pervasive challenge with analysis dependent on pedestrian, bicycle, and vehicular count data is the issue of data quality and format. Methodologies and data standards can vary from city to city and jurisdiction to jurisdiction; this chapter used a combination of national (Census, LEHD) data sets and local (Minneapolis traffic) data. Some cities, such as Boston, do not have robust pedestrian and bicycle counting programs throughout the city; others, such as Philadelphia, may have varying data release and non-disclosure agreements between MPOs, cities, and police departments; still other cities may have inconsistent data tracking and release practices, such as Washington, D.C. Such hurdles can make the collection and processing of pedestrian and bicycle spatial use data on a national scale exceedingly difficult. Better standards of practice in data collection, management, and distribution are needed.

However, with pedestrian activity estimation based on sampling existing counts, access analysis, and betweenness centrality of the underlying network, it becomes possible to predict the landscape of pedestrian activity within the urban area. Such techniques may prove important in informing urban planning processes and decisions, pedestrian safety programs, and highlighting areas of the city that experience higher pedestrian activity as salient areas for fine-grained attention to built environment details. An important extension of the identification of intersections with higher potential pedestrian traffic is the visualization of such areas – e.g. downtown. We can reasonably expect certain levels of pedestrian traffic, even where counts may not exist.

8

Which Station? Access Trips and Bikeshare Route Choice

Jessica Schoner and David Levinson

Abstract:
This chapter examines how people integrate bikeshare trip segments into their daily travel by studying how people navigate from place to place using the Nice Ride Minnesota bikeshare system in Minneapolis and St. Paul. We develop a theoretical model for bikeshare station choice inspired by research on transit route choice. We then model people's choice of origin station using a conditional logit model to evaluate their sensitivity to time spent walking, deviation from the shortest path, and a set of station amenity and neighborhood control variables. People prefer to use stations that do not require long detours out of the way to access. However, commuters and non-work travelers differ in how they value the walking portion of their trip, and what station amenities and neighborhood features increase a station's utility.

Introduction

Keywords: Bicycle sharing; Station choice; Route choice; Navigation; Nice Ride Minnesota

Bicycle sharing systems are an emerging trend globally. Companies are now hoping to be profitable. Users find the ability to have bicycle access on demand valuable. Cities are jumping on the trend in response to promises that bikeshare will induce mode shift, alleviate congestion, promote active and healthy lifestyles, and spawn economic development. However, as cities embrace the systems, our understanding about how people actually integrate these systems into their daily travel is limited.

The interest in, and use of, bikesharing has exploded in recent years. From numerous false starts, station-based,[1] and more recently dockless (station-less) bikesharing systems have rapidly grown in most markets they have entered, with a few notable retreats in bicycle-hostile areas like Sydney.[2] Bikeshare systems are perhaps the first mode about which there exists such extensive electronic tracking of every individual use of the system from origin to destination, and so provides a wealth of data for transport analysts to consider.

[1] (Beroud 2007, Parkes et al. 2013, Schoner et al. 2016, Shaheen et al. 2010; 2011).

[2] (Heymes 2019).

Issues have arisen with regard to system balancing (ensuring bikes are where they need to be),[3] predicting usage and effects on other modes,[4] understanding the destination choice,[5] and route choice of users.[6] There has also been interest in economic impacts associated with bikesharing.[7]

[3] (Pan et al. 2019, Singla et al. 2015).

[4] (Schoner and Lindsey 2015, Schoner et al. 2014, Sohrabi and Ermagun 2021)

[5] (Faghih-Imani and Eluru 2015).

[6] (Khatri et al. 2016).

[7] (Wang et al. 2015).

Bikeshare is an on-demand system: bicycles are available at any time of day or night. Despite this temporal difference with transit, the spatial structure of a person's route through the system is similar.

Bikeshare trips, like transit, are comprised of three primary segments:

1. Station (pick-up point) access walking trip.
2. One or more on-bicycle segments between stations.
3. Station (drop-off point) egress walking trip.

These segments are by definition anchored to two or more of the stations within the system. Because of this similarity, research about accessing transit stations provides some guidance to bikeshare.

Several studies have explored mode choice for the station access and egress segments of transit trips, while assuming the station choice is fixed.[8] Despite leaving out this station choice element, these studies provide insight into how people value travel time between several access modes to the station. Given that one component of bikeshare station choice is how people relatively value travel time spent walking versus biking, these findings are interesting. Chalermpong et al. found that the cumulative share of travelers arriving at a station by motorcycle taxi overtakes walking at about 0.7 km from the station, and increases drastically beyond 0.9 km from the station.[9] Hsiao et al. reported on what share of passengers using a transit station walked from a range of distances.[10] Notable drop-offs occur at 0.25 miles (about 400 m) and 0.75 miles (about 1,200 m).

[8] (Chalermpong and Wibowo 2007, Hsiao et al. 1997).

[9] (Chalermpong and Wibowo 2007).

[10] (Hsiao et al. 1997).

Guo et al. modeled subway commuters' station egress routes of Boston subway commuters from an on-board transit survey.[11] They identified two possible paths for each participant: One where the traveler may avoid a transfer by having a longer walk time, and another where the traveler transfers between routes and has a shorter walk time. Because the paths originated from different transit stations, route overlap between paths was minimal, avoiding the Independence of Irrelevant Alternatives condition that challenges many route choice studies. They found that paths through Boston Common (open space/parkland) increased the utility of the trip by 2.9 minutes, while paths through hilly terrain decreased utility by 3.5 minutes. Collectively, all their pedestrian environment variables increased pedestrian utility by about 21 to 33%, shifting the balance of how many people would choose the longer walking path based on travel time advantage alone.

[11] (Guo 2009).

Further underscoring the importance of relative durations of walking and bicycling is research into how transit passengers perceive time spent in different stages of their trips.[12] Bovy et al. address this in their study of transit route choice.[13] They model each segment, including the access and egress trips, station choice, and main route segment using a set of multi-nested generalized extreme value (GEV) models. The station choice component of their models focused on the caliber of service provided there: inter-city or local.

[12] (Wardman 2004).

[13] (Bovy and Hoogendoorn-Lanser 2005).

Through this chapter, we fill some of this knowledge gap by studying how people navigate from place to place using Minnesota's Nice Ride bikeshare system in Minneapolis - St. Paul area.

Questions

This chapter addresses the question:

- What factors affect which origin location (station) will be chosen for bikeshare trips?

It considers the time required to walk to the station, trip directness, the ratio of walking to trip time, and other built environment and socio-economic factors.

Methods

Theoretical model of station utility

Unlike transit, the user has significantly greater flexibility to choose stations and routes in between that satisfy her preferences for travel time savings, minimizing (or possibly maximizing) physical exertion, or even just a pleasurable riding environment.

Figure 8.1 maps a hypothetical scenario with several bikeshare stations and several transit stations connecting the same true origin (TO) and true destination (TD). This illustrates the system's flexibility, and underlines how complex this makes the study of bikeshare user route choice. The traveler could use any of the three closest bikeshare stations. The closest station requires walking away from the destination for a short distance. The most direct station is also the farthest away and would require the most walking. Finally, the third nearby station demonstrates additional station amenities that may make the station more attractive. In this scenario, the bike ride along the park may be more comfortable or easier than the bike ride along the main street. As a point of comparison, only a few of the nearby transit stations are appropriate for the trip between TO and TD, as many are either connected to the wrong route or the wrong direction of the correct route.

Relative station position

For the station choice scenario, let us temporarily assume that utility is derived solely from travel time savings, not from station amenities or individual characteristics. These other factors will be included in the final model, but the conceptual framework is easier to visualize by focusing strictly on travel time. A trip is comprised of a walking segment from the individual's origin to their originating station, a bicycling segment from the originating station to the arriving station, and another walking segment from the arriving station to the individual's destination. Since we are focusing strictly on station origins in this chapter, the second and third segments will be regarded as one.

As shown in Figure 8.1, when an individual starts a bikeshare trip, they may have several nearby stations to choose from. These stations vary in distance from the individual's origin, distance to the individual's destination, and the amount of deviation from a

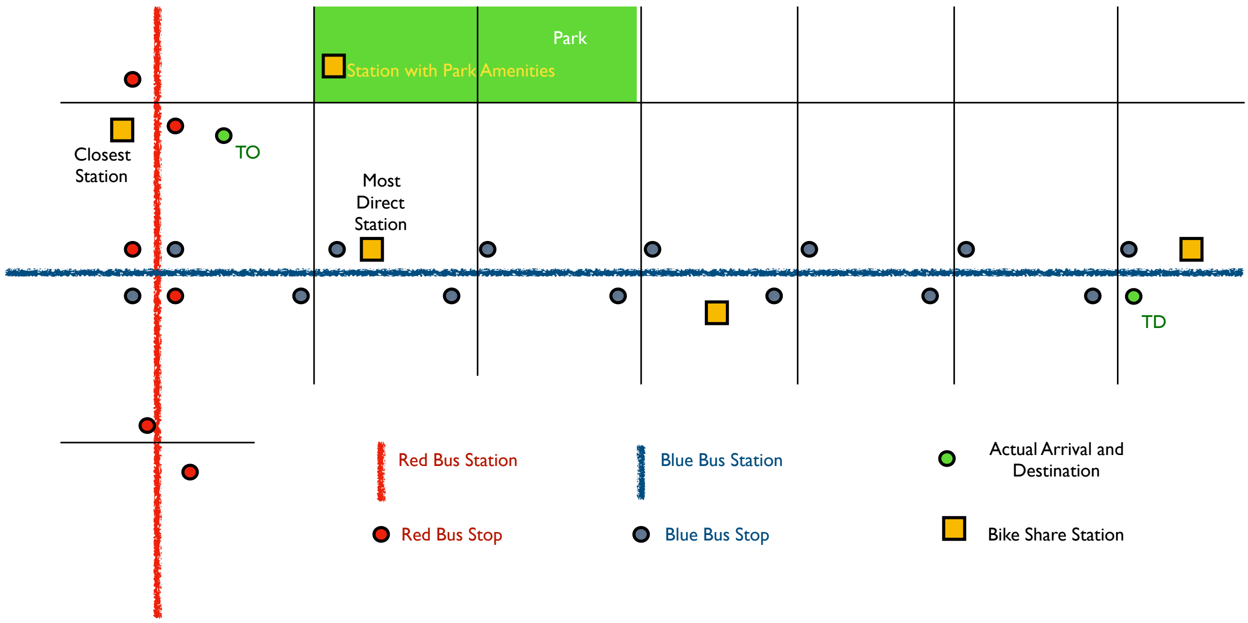


Figure 8.1: Hypothetical transit stations versus bikeshare stations. Any of the bikeshare stations can be used to travel from *TO* to *TD*, but only a small number of bus stops are eligible.

"shortest path" route between the origin and destination that is required to utilize that station.

Depending on the individual's relative walking and bicycling speeds and their respective preferences for each mode, they may be faced with a decision to walk to the closest station which requires detouring from the shortest path, or else walking a longer distance to use a station that minimizes overall travel distance.

Figure 8.2 shows three sets of equal travel time boundaries that vary with walking and bicycling speed. These boundaries show the relative value of retrieving a bicycle from the closest station versus walking farther in the direction of travel. Figure 8.3 shows one of these boundaries overlaid on a hypothetical grid network.

An individual starting from position *TO* (true origin) to position *TD* (true destination) with an average walking speed w and average bicycling speed b, assuming a grid-like street network, will find that they achieve equal travel time by selecting a station anywhere along one of the boundaries that corresponds to their travel speed.

For the 2-mile trip from *TO* to *TD* in Figure 8.2, consider the station located at position S_3, halfway between the origin and destination and directly along the shortest path of travel. An individual with $w = 3$ mph (about 5 km/hr) and $b = 12$ mph (about

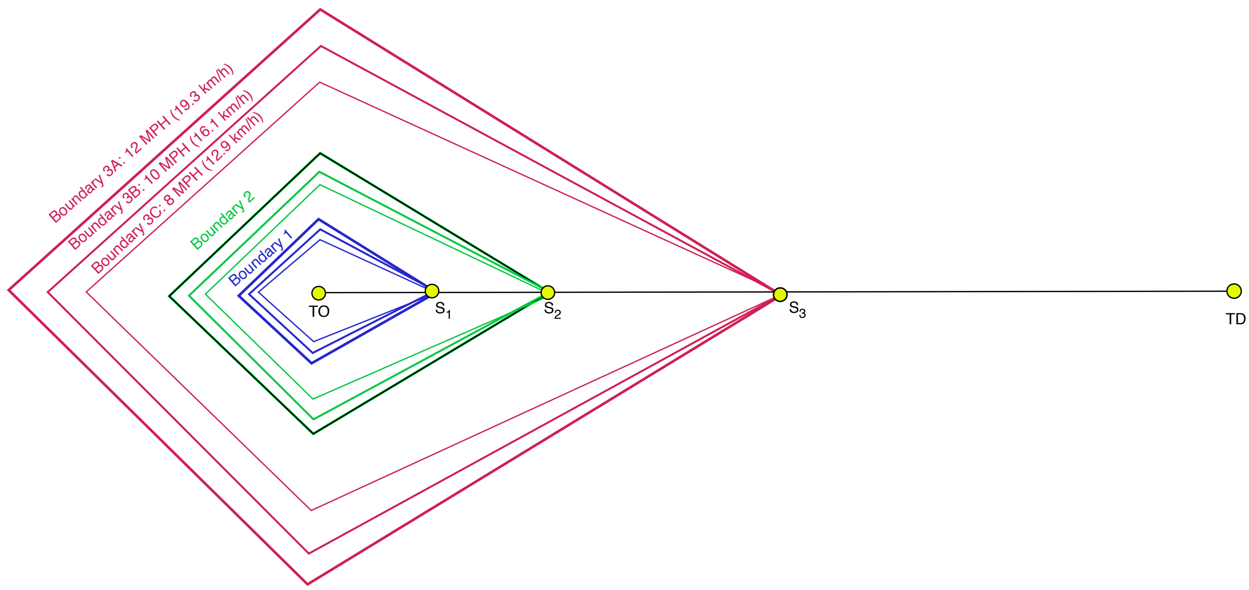


Figure 8.2: Theoretical equal travel time boundaries. A person starting at *TO* experiences equal travel time if they use station S_3 or any other station placed along Boundary 3A, 3B, or 3C depending on their travel speeds.

19 km/hr) can achieve equal travel time by either walking one mile east to retrieve a bicycle and biking the remaining mile, or walking 0.6 miles west, even though the latter alternative increases their overall travel distance by more than 1/3.

Conditional logit choice model

Given the complexity of variables potentially influencing a person's choice of station, the conditional logit model structure is a natural fit for the data.[14] The stations available to each participant are not ordered, ranked, or labeled in a way that would be conducive to multinomial logistic regression. The choice set for each participant is unique to their origin, so the stations are identified solely by their attributes as they relate to the individual and their trip.

[14] (McFadden 1973).

Survey

The data come from an online survey of Nice Ride Minnesota bikeshare subscribers conducted as part of another study about economic activity around bikeshare stations.[15] Nice Ride Minnesota emailed an introductory letter and survey link to 3,693 monthly and

[15] (Schoner et al. 2012, Wang et al. 2015).

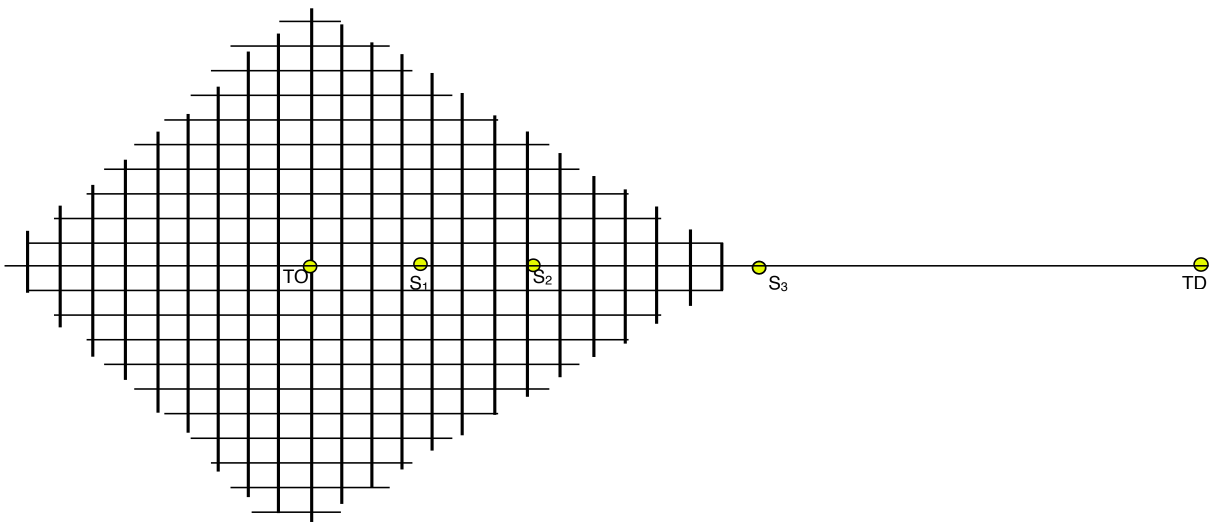


Figure 8.3: Theoretical equal travel time grid. A station placed anywhere on the grid network will provide equal or better travel time access between *TO* and *TD* as station S_3.

annual subscribers in May 2012. We received 1,197 valid surveys, for a response rate of 30%.

The survey focused primarily on aggregate trip behavior, such as the frequency with which the respondent visited various types of destinations via Nice Ride. The final section of the survey invited respondents to report the geographic details of specific trips they recently completed using Nice Ride bikes. These records captured the respondent's origin, the station they used at the beginning of their trip, the station at which they returned their bike, and their final destination, along with a verbal description of the route each participant rode and the purpose of the trip. A copy of the survey instrument used to collect trip records is available.[16]

[16] See (Schoner et al. 2012).

In the end, 597 respondents agreed to complete the final section and report one or more (up to five) trips. These records were manually geocoded using a combination of Google Maps and ESRI ArcGIS 10.1. Each trip record contained three or more segments: a station access segment between the respondent's origin and the originating station they used, one or more bicycling segments between stations, and another station access segment between the final station and the respondent's destination. Due to the open-ended questions used in the survey instrument, many trip

Table 8.1: Frequency of choosing the i^{th} closest station

Rank i	Not Chosen	Chosen	Pct. Chosen	Cum. Pct.	Total
1	90	418	82.6%	82.6%	508
2	447	57	11.3%	93.9%	504
3	493	18	3.6%	97.4%	511
4	496	6	1.2%	98.6%	502
5	509	1	0.2%	98.8%	510
6 to 10	2,534	5	1.0%	99.8%	2,539
11 to 20	4,912	1	0.2%	100.0%	4,913
> 20	20,563	0	0.0%	100.0%	20,563
Total	30,044	506	100.0%	100.0%	30,550

records were incomplete or unidentifiable. The resulting data set contained 506 complete trip records. An additional 10 were removed because their trip started and ended at the same location (round trip).

Choice set

Each geocoded trip was matched to the specific stations that the participant used. OpenTripPlanner's batch analyst tool was used to calculate the distances between all stations and each person's origin and destination. Trips were then flagged by whether they used the closest station to their origin, or another station. Table 8.1 shows the frequency of people starting their trip by using the i^{th} closest station. As the table shows, the vast majority of trips (82.6%) use the station closest to the origin, and 98.8% of trips use a station ranked 5$^{\text{th}}$ or closer. Therefore, we constrained the choice set to include only the five closest stations to each origin, measured in minutes walking at 5 km/hr. The dependent variable is a binary indicator of whether that particular station is the one that the traveler used as part of their trip.

Explanatory variables

A summary of the explanatory variables is available in Table 8.2. A simple t-test results shows which variables have a significant difference between the stations people chose as parts of their trip and the stations that were selected to comprise each person's choice set.

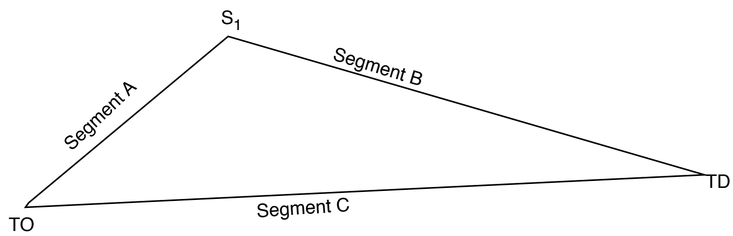


Figure 8.4: Measuring deviation (D) from shortest path. Shortest Path = C. $D = (A + B) - C$

MEASURES DERIVED FROM TRIP LENGTH. The length and duration of each trip segment in the choice set was measured using OpenTripPlanner's Batch Analyst and street network file downloaded from OpenStreetMap. Batch Analyst uses an algorithm to identify the shortest path between sets of origins and destinations and calculates a travel time. We assumed a walking speed of 5 km/hr (3.1 miles per hour) and a bicycling speed of 16 km/hr (10 miles per hour).

The travel time (in minutes) from the participant's origin to each station in their choice set was included in the model. Additionally, a ratio of walking time to total trip time (walking + biking) was included. These two variables capture people's absolute and relative preferences for time spent walking versus biking.

The straight-line distance between the true origin, stations, and true destination was calculated in meters using PostGIS. A measure of deviation (D) from the shortest path was calculated by subtracting the direct distance between origin and destination (C) from the combined distance of origin to station (A) and station to destination (B), as shown in Equation 8.1. Figure 8.4 shows these segments on a hypothetical trip.

$$D = (A + B) - C \tag{8.1}$$

STATION AREA AMENITIES. The presence of a bike trail and proximity to parks were included in the model to identify whether station area amenities increased the utility of a particular station. Trails are measured with a dummy variable for whether a bike trail passes through a 400-meter ($\frac{1}{4}$−mile) network distance buffer around each station. Proximity to park land is measured in meters.

		Chosen stations		Non-chosen set		Significant
	Variable Definition	Mean	(S.D.)	Mean	(S.D.)	Difference
C	Chosen station (Dependent Variable)					
W	Walk Time to Station (minute)	2.83	(2.77)	10.00	(6.09)	***
R	Ratio of Walk to Total Travel Time (%)	25.19	(18.25)	55.00	(17.28)	***
D	Deviation from Shortest Path (m $*$ 100)	1.31	(1.87)	5.48	(5.28)	***
T	Trail within 400m of station [1,0]	0.41	(0.49)	0.33	(0.47)	***
P	Distance to Park (m) $*$ 100	2.13	(1.67)	2.26	(1.79)	*
V	Violent crime rate per 10,000 people	61.39	(76.75)	56.54	(70.43)	*
M	Median Household Income (USD $*$ 1,000)	\$47.87	(\$24.63)	\$46.78	(\$24.07)	

Note: * $p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Table 8.2: Variable names, units, and summary statistics for all variables included in modeling. The final column shows the results of a t-test comparing chosen stations to stations selected to be in the choice set for each person.

Neighborhood characteristics. Crime rates and median household income were added to control for social variables that may encourage or discourage a person from using a particular station. Local crime statistics from the Minneapolis and St. Paul police departments were measured at the neighborhood level as the number of violent crimes that occurred per 10,000 people in 2010. Each station assumes the crime rate of the neighborhood that contains it. While neighborhoods are a much coarser resolution than preferred, data were not available in a more disaggregated format. To account for Downtown Minneapolis having both the highest crime rate and the largest concentration of stations and bikeshare activity, an interaction variable between crime rate and Downtown was created. The model includes a measure of crime rate *outside* the central business district only. Median household income is similarly measured at the neighborhood level, with the station assuming the median income of the neighborhood that contains it.

Trip purpose. Trip purpose can change the priorities people have while traveling. Someone on their morning commute may prioritize travel time savings above all else, whereas someone taking a bike out on their lunch break to get some fresh air may value other characteristics. To account for this possible difference, we modeled commute trips and non-work trips separately.

Individual characteristics. Data about each member's age and gender were available from electronic trip records provided by Nice

Ride for matching with survey data. Several interaction variables between age, gender, and the walking and deviation variables were tested and ultimately excluded due to insignificance.

Findings

Model fit

Table 8.3 shows the results from modeling station choice for commute and non-work trips. The 'Base Model' includes only the walking and deviation variables. The "Full Model" controls for proximity to a bike trail and parks, crime rates for stations outside the CBD, and median household income in the neighborhood containing the station. The final column shows a more parsimonious model where control variables with p-values greater than 0.1 were removed stepwise in order from highest p-value to lowest, followed by walking or deviation variables under the same criteria.

McFadden's Pseudo $-R^2$ and Bayesian Information Criterion (BIC) are reported for all models. The commute models have Pseudo $-R^2$ values ranging from 0.724 to 0.758. The non-work trips have slightly lower Pseudo $-R^2$ values, from 0.700 to 0.708, possibly because people experience greater time pressure on commute trips, and other amenities matter less in station choice. Overall, these values are high, suggesting that the fitted models are all substantial improvement over the null models. In both commute and non-work trips, most of the improvement over a null model comes from the walking and linear deviation variables. Controlling for station amenities and neighborhood characteristics provides only a marginal improvement. BIC assesses model fit with a specific emphasis on penalizing the addition of superfluous variables that marginally improve the log-likelihood without contributing any meaning. The BIC for both commute and non-work trips suggest that the additional parameters in the full model do not add significant value, and either the base model or final model are preferable.

Commute trips

Travel time to the station, deviation from the shortest path, proximity to parks, and crime outside the CBD are all significantly

	Model 1				Model 2				Model 3			
Variable	Coeff	(SE)	OR	Sig	Coeff	(SE)	OR	Sig	Coeff	(SE)	OR	Sig
Work Trips												
W Walk to Station (minutes)	-0.559	(0.233)	0.572	**	-0.557	(0.263)	0.573	**	-0.741	(0.120)	0.477	***
R Ratio of walking to trip time	-0.018	(0.037)	0.982		-0.036	(0.045)	0.964					
D Deviation (m * 100)	-0.162	(0.095)	0.850	*	-0.212	(0.107)	0.809	**	-0.201	(0.100)	0.818	**
T Trail within 400 m					0.267	(0.550)	1.306					
P Distance to Park (m * 100)					-0.411	(0.198)	0.663	**	-0.417	(0.185)	0.659	**
V Crime (outside CBD)					-0.007	(0.004)	0.993	*	-0.006	(0.003)	0.994	**
M Median Income ($ * 1,000)					-0.013	(0.015)	0.987					
N Chosen (Choices)				97 (485)				97 (485)				97 (485)
McFadden's Pseudo-R^2				0.724				0.758				0.751
Bayesian Information Criterion				104.730				118.894				102.500
Non-work Trips												
W Walk to Station (minutes)	-0.117	(0.089)	0.890		-0.113	(0.092)	0.893					
R Ratio of walking to trip time	-0.083	(0.017)	0.920	***	-0.089	(0.018)	0.915	***	-0.108	(0.008)	0.897	***
D Deviation (m * 100)	-0.303	(0.046)	0.738	***	-0.296	(0.047)	0.744	***	-0.327	(0.042)	0.721	***
T Trail within 400 m					0.129	(0.272)	1.138					
P Distance to Park (m * 100)					-0.118	(0.082)	0.888					
V Crime (outside CBD)					-0.003	(0.002)	0.997	**	-0.003	(0.002)	0.997	**
M Median Income ($ * 1,000)					-0.011	(0.007)	0.989	*	-0.013	(0.007)	0.988	*
N Chosen (Choices)				394 (1,970)				394 (1,970)				394 (1,970)
McFadden's Pseudo-R^2				0.700				0.708				0.705
Bayesian Information Criterion				402.622				423.060				404.387

Note: $p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Table 8.3: Conditional logit model results of origin station choice for commute and non-work trips

associated with choosing a particular station at the beginning of a commute trip. The conditional logit regression coefficients represent the change in log-odds of choosing a station based on a 1-unit change in the independent variable, so the odds ratios are also presented for ease of interpretation. In the final model, each additional minute required to walk to a station is associated with a -0.741 decrease in the log-odds of choosing that station. Put another way, that station is 47.7% as likely to be chosen as one that is one minute closer.

Interestingly, the absolute measure of walking (minutes) is significant in the final model, but the ratio of walk time to total trip time disappears. The deviation from the shortest path variable is also significant. From this we can infer that commuters value shorter trips, and have a threshold above which they prefer not to walk. But the relative balance of walking and bicycling in any given trip is irrelevant, as long as the travel times meet the other criteria.

Proximity to parks appears to be an important factor.[17] For commuters, the park may increase the station's utility by making the walk to and from the station more pleasurable. Alternatively, it

[17] Consistent with (Guo 2011).

could simply be a function of home-based commute trips starting in residential areas that have better park access in general.

Non-work trips

Like commute trips, deviation from the shortest path and crime rates for stations outside the CBD are significant. For non-work trips, however, the relative amount of walk time seems to be more important than an absolute threshold of minutes. People making non-work trips prefer to spend most of their travel time on the bicycle rather than walking to the station. A station for which the walk segment comprises a 1-percentage point larger share of the total trip time is only 89.7% as likely to be chosen.

The negative sign on the income variable is curious. Given the demographics of Nice Ride users - higher income, highly educated, young professionals - one would expect stations in higher income neighborhoods to have a higher utility. However, this suggests that a marginal increase in the income level of the neighborhood actually decreases the likelihood for stations within that neighborhood. This could be a function of where Nice Ride subscribers tend to live. Although their demographic profile suggests higher income, they may be more likely to live in diverse neighborhoods than exclusively wealthy areas, so stations in these areas would get more use.

A station with an increase of one violent crime per 10,000 people has a subtle disadvantage (99.7% as likely to be chosen), but rescaling the variable makes the effect more noticeable. A station in a neighborhood with 64 more violent crimes per 10,000 people (the standard deviation of crime rate in this sample) has an odds ratio of 81.9%.

Conclusions

The findings from this chapter will be important for practitioners considering or already managing bikeshare systems.

Relative preferences for biking over walking. The models for commute trips and non-work trips found preference for shorter walking segments, both in absolute terms (minutes walking to the station), and relative terms (ratio of walk time to overall trip time). The relative value of walking and biking times versus distance can

inform decisions about station spacing and network expansion. A strong preference for time spent biking over walking suggests that a denser network may enable people to decrease these walking segments.

While spacing stations (or geofenced bikeshare pickup/dropoff points for dockless bikes) along a route would enable people to walk in the direction of their destination to pick up a bike, given the preference for time spent biking, clustering stations near where people are starting and ending their trips may make more sense.

The preference for longer biking durations relative to walking suggests that the pricing structure that discourages longer bike trips may be undermining the utility of the system somewhat. In situations where people are faced with a decision about taking a longer trip that is comprised of a larger share of biking time, the typical pricing structure that starts charging trip fees beyond 30 minutes may deter ridership.

HOW FAR PEOPLE WALK TO ACCESS STATIONS. More fundamentally than the tradeoffs between walking and biking time and overall distance, this chapter helps us learn how far people walk to stations in general. There is no control group of people who didn't make a trip to advise how far is too far, but there is at least evidence that the vast majority of people prefer to use the closest station. With future research, this may help with forecasting or anticipating demand by providing an appropriate catchment area size for each station.

STATION AMENITIES AND NEIGHBORHOOD ATTRIBUTES. Unlike an aggregate model of station use,[18] this chapter measures how individuals choose which stations to use. The aggregate model estimates the value of station amenities and nearby businesses as trip generators and attractors. But in this chapter, the station choice is assumed to be to some extent independent of the trip purpose, and only dependent on the origin and destination spatially (with the exception of commute trips or other trip purposes that constrain time). The findings from the regression models in this chapter identified the disproportionate importance of parks for commute trips. Stations closer to parks were more likely to be chosen, all else equal. The importance of parks for commuters may ease tension within bikeshare system administration about planning for regular

[18] Such as (Schoner et al. 2012).

long-term members versus recreational short-term users who generate more revenue.

Next

This chapter presents several notable opportunities for future research. The data came from the Nice Ride Minnesota system, a mid-sized bikeshare network with well-managed station balancing efforts. Because network congestion is not an issue here, uncertainty variables such as station capacity and probability of being empty or full when a traveler needs a bicycle were not included. The results from this chapter will therefore be more applicable to small- and medium-sized cities with a similar operations context.

Another limitation is the unit of analysis for neighborhood attribute variables. Crime reports are not available at any level finer than a neighborhood, but this means that many participants' entire choice sets may fall entirely within a single neighborhood, so that all the nearby stations have the same measure of crime rate. Median income was evaluated at the same level as crime rate for consistency, but is available at smaller levels of aggregation. Future analysis might consider removing the crime variable, measuring income levels at the block group or census tract level, and adding other neighborhood spatial variables.

This chapter establishes a framework for evaluating route choice in bikeshare trips. The empirical model focused strictly on the station access component, but future research should consider the egress segment and the bicycling route as well.[19] Some of the examples from transit literature[20] provide a starting point for jointly estimating these components.

[19] (Schoner and Levinson 2014).

[20] See (Bovy and Hoogendoorn-Lanser 2005).

9
Cargo Bikesharing as a Last-mile Connector

David Duran-Rodas, Aaron Nichols, and Benjamin Büttner

Abstract:
This chapter proposes the integration of cargo bikes into the existing bikesharing infrastructure to make active access to urban e-commerce infrastructure (UEI), which includes post offices and parcel post offices, more competitive. This chapter conducts a spatial fairness assessment to analyze which social groups are favored with active access to UEI in Munich, Germany. This evaluation is conducted using four scenarios: (1) access to post offices, (2) access to post offices and parcel lockers, (3) access to post offices and parcel lockers with an integration of station-based cargo bikesharing, and (4) access to post offices and parcel lockers with an integration of free floating cargo bikesharing. E-commerce infrastructure in Munich primarily benefits the cosmopolitan population, regardless of social status. If cargo bikesharing were integrated into the system, the distribution of UEI would follow a mix of spatial equity and efficiency criteria.

Introduction

In the past years, there has been a remarkable increase in electronic commerce (e-commerce).[1] E-commerce refers to the commercial transaction of goods or services through an electronic medium, mainly the Internet.[2] It offers benefits to customers, such as the ability to conduct transactions 24 hours, every day of the week. In addition, customers have a wider range of options, allowing them to compare and choose a more convenient option based on previous

Keywords: Bike sharing; Parcel lockers; Equity; Cargo bike; e-commerce; Social justice; Accessibility; Urban freight; City logistics

[1] (Eurostat 2021, Pantelimon et al. 2020, Vakulenko et al. 2019, Viu-Roig and Alvarez-Palau 2020).

[2] (Eurostat 2021).

reviews as well, and it could lower the cost of products and make them affordable for less affluent people.[3] In 2018, about 21% of businesses in the EU made electronic sales, an increase of about 9% compared to 2011.[4] Germany is among the European countries with the highest number of online shoppers, along with the United Kingdom and France.[5] In 2019, around 88% of the German population made purchases online.[6]

E-commerce growth has led to an increase in urban "last-mile" logistics.[7] Last-mile delivery incurs extra costs[8] and causes higher volumes of commercial vehicles in urban areas.[9] When the last-mile delivery is directly to homes, it has the disadvantage of fewer consolidated deliveries, higher miles traveled, more stops, and absence at the time an order is delivered.[10] Although the emergence of crowdsourced delivery has remedied some of the last-mile delivery issues,[11] an alternative to home delivery is still that customers pick up or drop off their goods at locations other than home such as parcel lockers or pick up points.[12] We call these last two options urban e-commerce infrastructure (UEI).

UEI provides better access to goods purchased online, and is an efficient system for condensing delivery and minimizing freight miles traveled, thus reducing emissions, noise, accidents, energy consumption, and costs.[13] which could lead to a higher quality of life and more livable cities. However, potential negative externalities of last-mile travel to UEI by customers may be amplified depending on how people access them.[14]. In Brussels, Belgium, nearly half of the respondents collected their goods by car, about 20% used public transport, and the same number walked, while only 9.1% biked.[15] Similarly, in Poland, most of the goods purchased online were picked up by car,[16] as was also seen in five cities in Australia (61%).[17]

In 2020, the most common goods bought online in the European Union were clothes (including sport clothing), shoes or accessories (64%); deliveries from restaurants, fast-food chains, catering services (29%); and furniture, home accessories or gardening products (28%) (Eurostat, 2021). Given that, some of these items may be of a weight and size that a single person cannot easily transport on foot or on conventional bicycles from the UEI, and e-commerce could lower the cost of products and make them affordable to less affluent people,[18]. the question arises as to how heavy and large goods can be transported from UEI by people who do not have access to, cannot afford, or are unwilling to use a car.

3 (Vadwala and Vadwala 2017).

4 (Eurostat 2021).

5 (Seidel and Blanquart 2020).

6 (Edwards 2020).

7 (Ermagun and Stathopoulos 2020, Vakulenko et al. 2019).

8 (Van Duin et al. 2020)

9 (Vakulenko et al. 2019).

10 (Zhang et al. 2019).

11 (Ermagun et al. 2020, Punel et al. 2018).

12 (Viu-Roig and Alvarez-Palau 2020).

13 (de Oliveira et al. 2017, Holguín-Veras et al. 2018, Iwan et al. 2016, Lachapelle et al. 2018, Viu-Roig and Alvarez-Palau 2020).

14 (Iwan et al. 2016).

15 (Rai et al. 2020)

16 (Iwan et al. 2016).

17 (Lachapelle et al. 2018).

18 (Vadwala and Vadwala 2017).

Unlike private cars, picking up and dropping off goods at UEI with cargo bikes has the potential to mitigate emissions and costs, as well as the inconvenience of blocked sidewalks and bike lanes. Cargo bikes can actively transport heavier and larger goods in the last mile.[19] Due to their higher cost compared to traditional bicycles and the likelihood of low individual use of cargo bikes, in this chapter we propose integrating cargo bikes into the existing bikesharing infrastructure to make bicycling to UEI more competitive. Cycling has the potential to increase the catchment area for the last mile to UEI and thus more people would benefit.

[19] (Rudolph and Gruber 2017).

Questions

The amount of UEI should be bounded due to limited resources and space, and also, their wider distribution may lead to a higher number of vehicle kilometers driven due to a higher number of collection points. Therefore, their allocation must be limited either for private or public stakeholders. This chapter addresses the following question:

- If the allocation of UEI should be limited, who should have priority access to them in order to achieve a fair distribution?

Methods

The proposed methodology to meet the objectives of this chapter mainly follows three steps: (1) data collection, (2) delimitation of catchment area, and (3) spatial fairness assessment (Figure 9.1).

Data collection

Five main types of data are collected: street network, location of post offices and parcel lockers, bikesharing stations, and socio-spatial parameters (e.g., socio-demographic characteristics).

The road network and the location of post offices and bikesharing stations were collected from OpenStreetMaps.[20] Parcel locker stations were gathered from DHL's API server in Munich.[21]

[20] (OpenStreetMap contributors 2021).

[21] (DHL 2020).

Sinus milieus were selected as a social segmentation to compare access among different social groups. Milieus are a social classification of people including "orientations, their values, goals in life, lifestyles, and attitudes as well as their social background."[22]

[22] (SINUS Markt- und Sozialforschung GmbH 2018).

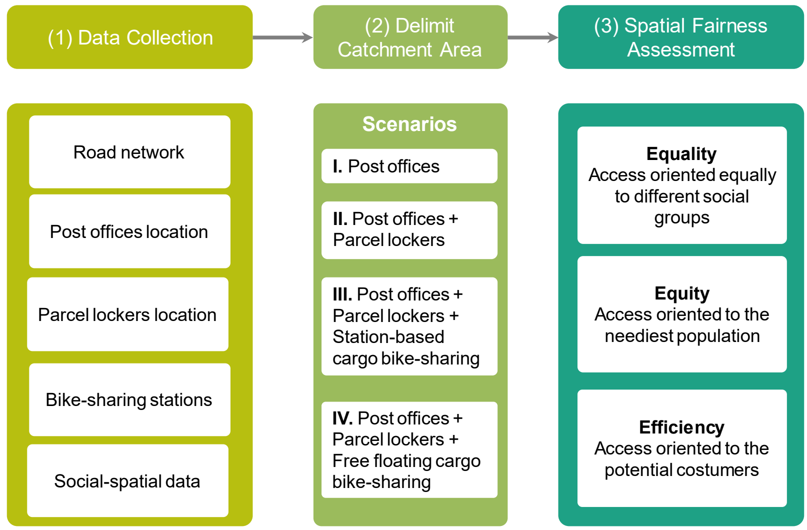


Figure 9.1: Three-step methodology: data collection, delimitation of catchment area, and spatial fairness assessment

Sinus milieus classify Germans into ten categories (Figure 9.2) along two dimensions: a) social status (education, occupation, income) and root values (tradition, modernization, re-orientation). The marketing companies Microm and Sinus conducted a micro-geographic segmentation by estimating a dominant milieu category for each of the 21 million addresses in Germany based on customer address databases and city statistics.[23]

In this chapter, we considered the Sinus Milieus as social segmentation instead of the traditional socio-demographic characteristics because they include the commonly used social status and also include an additional categorization, namely the root values. After considering the milieus, socio-demographic twins, i.e., people with the same socio-demographic characteristics, can be further clustered using the root values. If two socio-demographic twins prefer a product over another, the root values can be the differentiator for that decision.

This market segmentation was tested with "leading brand-name manufacturers and well-known service providers from politics, media and associations, as well as advertising and media agencies."[24] To the best of the authors' knowledge, this is the first attempt to use the marketing segmentation to assess who benefits from UEI.

[23] (SINUS Markt- und Sozialforschung GmbH 2018).

[24] (SINUS Markt- und Sozialforschung GmbH 2018).

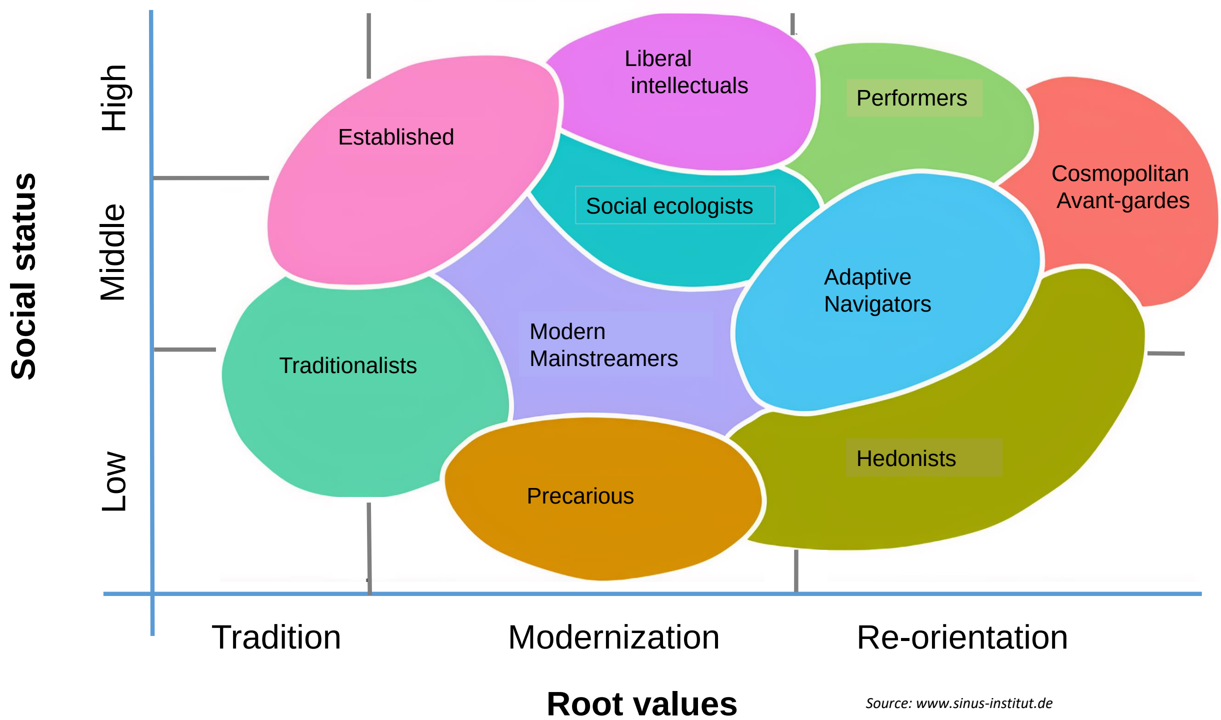


Figure 9.2: Sinus Milieus categories. Source: (SINUS Markt- und Sozialforschung GmbH 2018).

Delimitation of the catchment area

The city of Munich is the capital of Bavaria in the South of Germany. Munich is suffering thanks to its own success; headquarters of global players like BMW, Siemens, and MAN are attracting employers from all over the world. Two of Germany's highest ranked universities and no tuition fees are attracting international students. As a result, the city of Munich is trying to cope with an enormous population growth which is putting the existing infrastructure (e.g. congestion, emissions, overcrowded public transport) through a stress test.

In 2019, Munich's population exceeded 1.56 million on 310 km² which makes Munich the most dense German city before Berlin and Frankfurt am Main.[25] In line with this, Munich is also top ranked when it comes to the highest cost of living. Affordable housing and vulnerable population groups can mostly be found in the outskirts, which are typically characterized by low levels of public transport access.[26] E-scooter sharing as well as station based and free floating car and bikesharing is offered by multiple operators within the city of Munich. These free floating services are mostly limited to the

[25] (Landeshauptstadt Muenchen 2021).

[26] (Büttner et al. 2018).

inner city which is also characterized by a very dense public transport network; hence, at the moment these services do not provide a last mile solution in the outskirts.

Consequently, a fair distribution of amenities ensuring daily/basic needs (which in part can be fulfilled by e-commerce and UEI) is crucial for all social segments/milieus, which will be examined in the following analysis.

In this chapter, access to the UEI is referred to as the ease of traveling from the UEI to the destination (e.g. home) with a good purchased online. In other words, the access analysis includes trips from the UEI to a certain point in space but not the other way around. Therefore, the catchment area in this chapter is defined as the region where an average person is willing to walk, cycle, or both from the UEI to their destination after picking up an item purchased online.

Four scenarios are set to analyze the potential of increasing urban e-commerce infrastructure with parcel lockers and a potential integration of cargo bikesharing:

- **Scenario I. Post offices**. The first scenario includes the analysis of a catchment area shaped with the road network of a distance that a person is willing to walk to their destination after picking up an item purchased online from a post office.

- **Scenario II. Post offices + Parcel lockers.** The catchment area is formed with the distance a person is willing to walk to their destination after picking up an item purchased online from either a post office or parcel box.

- **Scenario III. Post offices + Parcel lockers + Stations-based bikesharing (SBBSS).** The third scenario includes the hypothetical case of integrating cargo-bikes in the existing station-based bikesharing infrastructure. In this scenario, the bikesharing system is based on stations. The trip from the UEI (post offices + parcel lockers) to the destination is hypothesized to be intermodal, combining walking and cycling. Therefore, the catchment area is estimated in terms of the travel time a person is willing to walk from the UEI to the bike station and then cycle to the destination. The estimation of the catchment area does not include the time for returning of the bike. The stations that are considered in this scenario are those within a walkable area from the UEI.

- **Scenario IV. Post offices + Parcel lockers + Free-floating bikesharing (FFBSS).** Finally, the fourth scenario considers the scenario of a free-floating cargo bikesharing system in a catchment area. Free-floating bikesharing allows for pick up and drop off of rental bikes anywhere in a public space within a service area.[27] The boundaries of the catchment are based on the travel time a person is willing to cycle after collecting the item at the UEI. This scenario assumes that the bikes are always available at the UEI and the trip for returning the bike is neglected.

[27] (Shaheen and Cohen 2019).

Figure 9.3 shows the catchment areas for the four different scenarios. These areas were delimited based on the existing road network and the maximum access distance using the "Service Area" delimitation feature of the open-source geographic information software QGIS 3.12.[28]

[28] (QGIS Development Team 2009).

In Brazil 70% of respondents are "willing to walk up to 1,000 meters (up to 15 minutes walking)" to pick up their goods from parcel lockers.[29] In this chapter, we preferred to be conservative and considered a 7-minute travel time since the scenario assumes large and heavy goods are being transported. Therefore, the catchment area is a 500 meter walking distance from the UEI (scenarios I and II) considering an average walking speed of 2.2 mph (3.5 km/hr), which is the average walking speed of elderly people in Germany.[30]

[29] (de Oliveira et al. 2017).

[30] (Schimpl et al. 2011).

For scenario III, which includes the integration of cargo bikes into the existing bikesharing stations, an intermodal 7-minute bike+walk trip increased the catchment area to around 1,300 meters. Travel time was simplified to 3.5 minutes to cycle to the bikesharing station and 3.5 minutes to walk to the UEI. This approach considered a cycling speed of 8.7 mph, which is the minimum speed used for timing bikes' traffic lights in Germany.[31] Catchment areas were expanded only if a bikesharing station is less than 500 meters (max. walking distance) away from the UEI. This distance is inferred that people are willing to walk the most from the UEI to the bike station. Finally, scenario IV, which includes an incorporation of FFBSS with cargo bikes, has a catchment area of 1,600 meters with a cycling time of 7 minutes.

[31] (Pucher and Buehler 2017).

There are a total of 119 post offices and 126 parcel lockers in Munich. Figure 9.4a shows the distance from each building in Munich to the nearest post office (scenario I) and to the nearest either post office or parcel locker (scenario II). Both scenarios show a similar mode of about 400 meters to UEI. However, the median

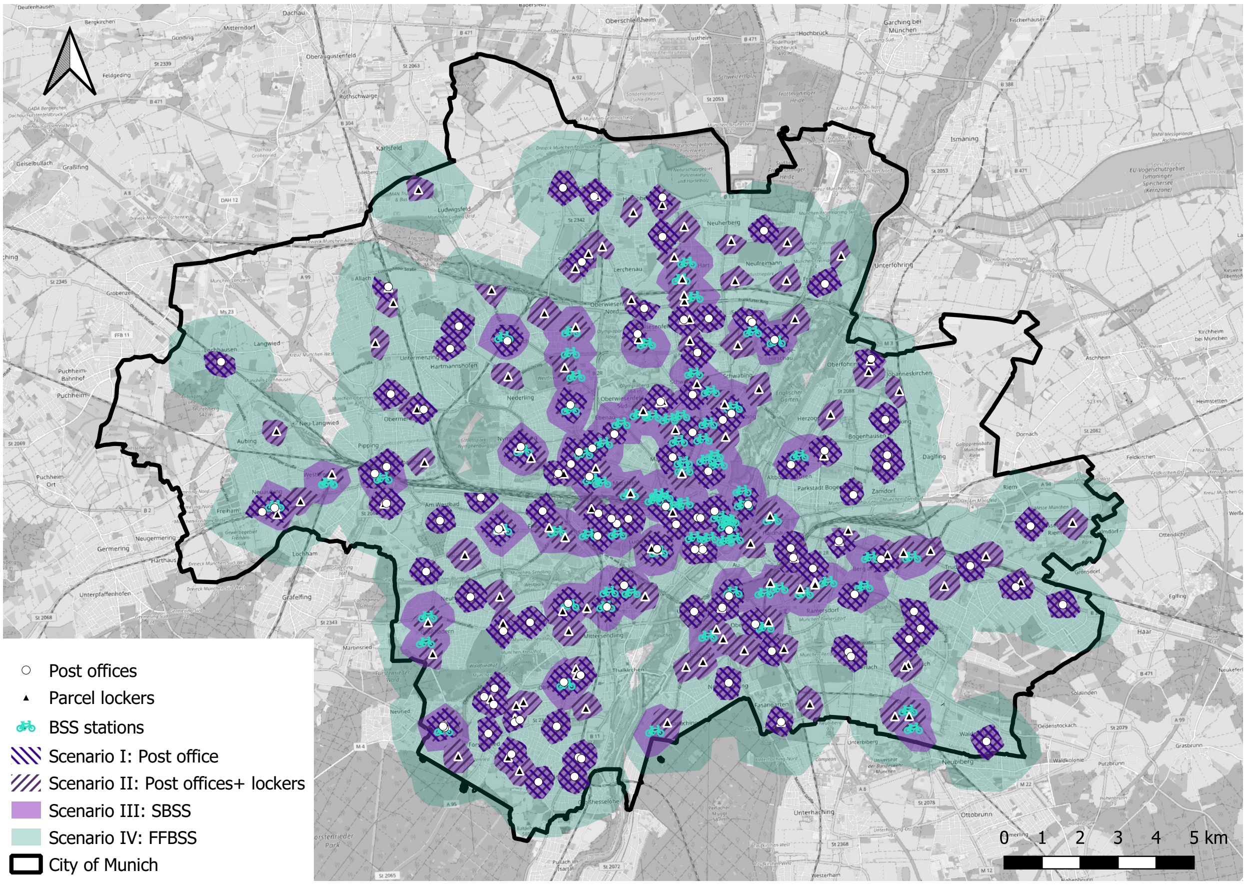


Figure 9.3: Catchment areas of the four scenarios

proximity decreases drastically and shows a lower standard deviation for scenario II compared to scenario I.

As shown in Figure 9.4b, the built up area and population served by the fourth scenario would include almost the entire population of Munich within the UEI catchment area. Furthermore, there was a linear upward trend with a positive rate of 22.02 in the prevalence of the population living in the catchment areas.

Spatial fairness assessment

Fairness is a subjective assessment in which a "fair" allocation of resources for some people might not be "fair" for others.[32]

Spatial allocation of resources may follow three criteria:[33]

[32] (Goldman and Cropanzano 2015).

[33] (Duran-Rodas et al. 2020, Leventhal 1976)

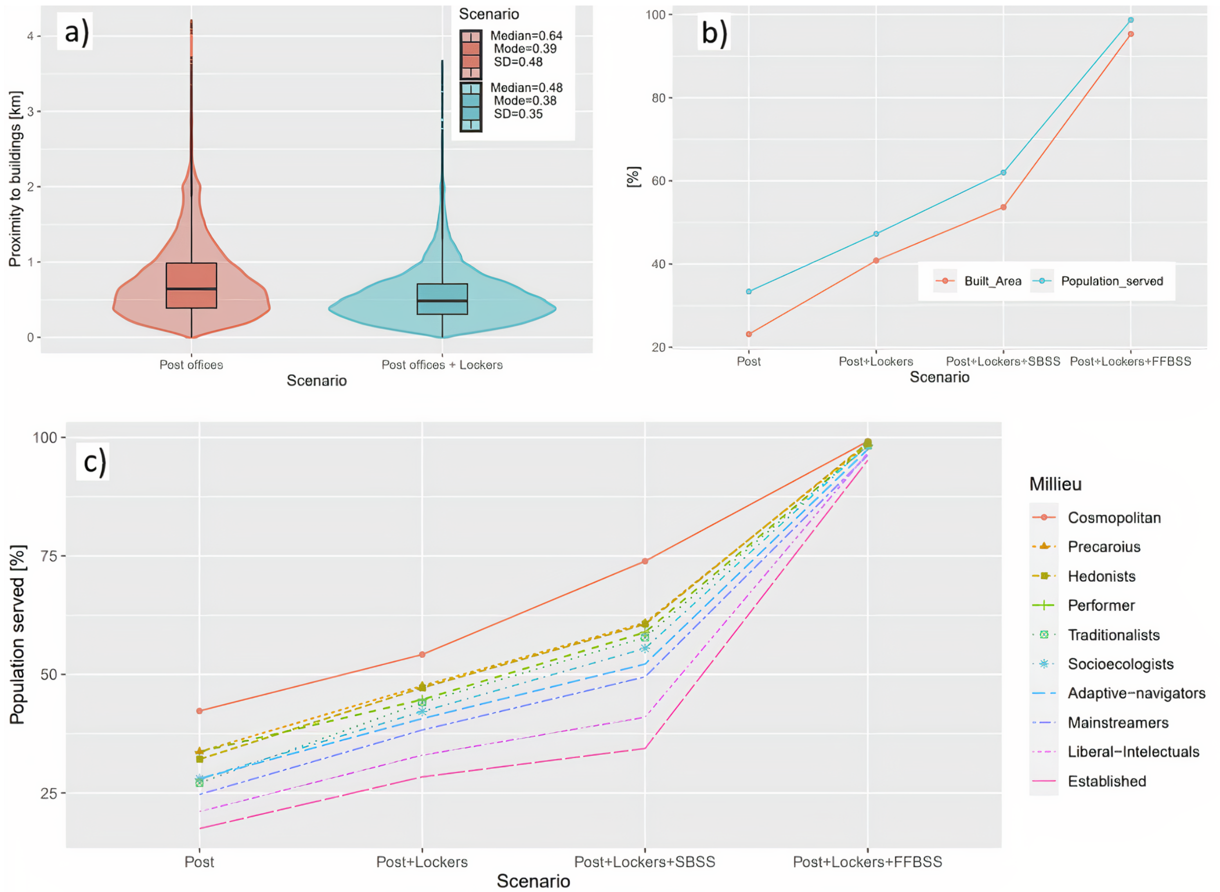


Figure 9.4: Urban e-commerce infrastructure spatial analysis: (a) Proximity of UEI to buildings, (b) Coverage area of UEI in the different scenarios, (c) Population served by UEI per social group and scenario

- Spatial equality, where resources are distributed evenly in the city or among social groups,
- Spatial equity, allocation is prioritized in areas with the highest need in terms of social status, income, opportunity, or ability,
- Spatial efficiency, allocation is prioritized in areas with the highest expected contribution or demand, i.e. those who are able and willing to pay get the resources.

It is worth highlighting the possibility of a mixture of equity and efficiency, where prevalence is simultaneously greater among the neediest social groups and among the market-oriented social groups.

If UEI contributes to having fewer emissions, congestion, noise, and less sidewalk parking, who gets these benefits in the city and

what distribution criteria does UEI follow? Was the UEI placed where the unprivileged population lives or where the most privileged people live? In this chapter, the assessment of the spatial distribution criterion followed for allocation UEI is called spatial fairness assessment.

This chapter conducts a spatial fairness assessment to analyze which social groups are favored in active access to UEI. In other words, to determine whether UEI distribution follows an allocation based on spatial equity, efficiency, or equality.

This evaluation is conducted using four scenarios:

- (I) access to post offices,
- (II) access to post offices and parcel lockers,
- (III) access to post offices and parcel lockers with an integration of station-based cargo bikesharing, and
- (IV) access to post offices and parcel lockers with an integration of free floating cargo bikesharing.

Based on the delimited catchment areas, the prevalence of different social groups living or working in these areas is estimated. Moreover, a comparison of the prevalence and its variation between four different scenarios is carried out to analyze which social groups are privileged in accessing UEI.

Findings

To find out which social groups (milieus) benefit from living in the different catchment areas, we estimate the prevalence of each scenario (Figure 9.4c). Cosmopolitans showed the highest prevalence in all scenarios, with a greater advantage in Scenario III, which integrated existing bikesharing infrastructure. It is worth highlighting that the Cosmopolitan population has the social characteristics identified by Rai et al. as potential users of parcel boxes.[34]

[34] (Rai et al. 2020).

The following groups with greater prevalence are low social status (Traditionalists, Precarious, and Hedonists). In contrast, high social status individuals with traditional orientation are served the least in comparison to the other social groups. From scenario III, this group showed the lowest rate of increase (Figure 9.4c).

A complementary analysis was carried out to compare the rates of the social groups with their prevalence in the whole city

Millieu	Munich Total (%)	I. Post office	II. Post + Lockers	III. Post+Lockers + SBSS	IV. Post+Lockers + FFBSS
Established	32.1	-9.6	-7.8	-9.0	-0.6
Liberal-Intelectuals	16.3	-2.6	-2.0	-2.3	0.0
Adaptive-navigators	8.7	+0.9	+0.6	+0.7	0.0
Performer	7.3	+2.5	+1.4	+1.7	+0.1
Mainstreamers	7.2	-0.1	+0.1	+0.3	0.0
Traditionalists	6.8	+0.5	+1.2	+1.4	+0.1
Hedonists	6.7	1.9	+1.7	+1.8	+0.1
Cosmopolitan	6.5	+4.5	+2.9	+3.5	+0.2
Socioecologists	4.3	+0.5	+0.5	+0.7	+0.1
Precaroius	2.7	+0.9	+0.7	+0.7	0.0
Average (abs)		*2.4*	*1.9*	*2.2*	*0.2*

Table 9.1: Comparison of the prevalence of social groups according to each scenario and the total population in Munich

(Table 9.1). Since scenario IV involves almost the whole city, the only missing groups to be included would be the Established milieu. As in the previous analysis, Cosmopolitans, Performers, and low social status milieus are advanced in the access to commerce infrastructure in scenarios I, II, and III. Another contribution of Table 9.1 is the average of the absolute values of the increasing or decreasing percentages. Equality is met when the changes follow a uniform distribution around zero or in other words a lower average.

As further results from the spatial fairness assessment, scenario II and III promote economic efficiency because they benefit those who are potential users, such as the Cosmopolitan or Performers groups. Moreover, the population with low social status is also favored in these scenarios, which means the spatial equity criterion is also followed. If some social groups are favored and others are not, it means that scenarios II and III do not follow spatial equality. However, the inclusion of parcel lockers (scenario II) in the analysis concludes in an increase in spatial equality (lower average) but it decreases when the analysis included the SBBSS scenario (scenario III). Finally, we can conclude that scenario IV follows a spatial equality criteria because it covers most of the population, and UEI serves all the social groups (average of change close to zero, see Table 9.1).

In summary, scenario IV follows spatial equality and scenarios II and III follow a combination of spatial equality and economic efficiency.

Conclusions

Four scenarios were created to assess which social groups benefit from access to the UEI. Post offices and parcel lockers (Scenario II) were found to have the potential to increase the efficiency and also benefit those less advantaged. Integration with station-based cargo bikesharing increased the catchment area in a similar proportion to parcel lockers. Therefore, the integration of cargo bikesharing in Munich (scenario III) has potential similar to the integration of parcel lockers (scenario II). It should be emphasized that in scenario II, approximately 50% of the population in Munich has acceptable walking access to UEI. In addition, the integration of cargo bike facilities at 83 stations would increase the population served to 60%. Finally, scenario IV, which considers the integration of free-floating cargo bikesharing, would represent the fulfillment of the service throughout the Munich metropolitan area, which at the moment is only available in the inner city (see section 3.1).

Investing in a cargo bikesharing system could help as an alternative to avoid the use and costs of motorized transport in the last-mile. In addition, this approach would reduce the need for parking spaces close to UEI sites. The question is whether cargo bikes could be integrated physically and also in terms of price, i.e., the cost of delivery would include the cargo bike rental. Thus, cargo bikesharing can make the active picking up of goods more attractive, so that people benefit from saving the cost of a public transit ticket or gasoline and parking for private cars. Moreover, for many people bicycling is fun and helps riders discover cities and people, it has the potential to save travel time due to congestion and thus emissions, it is independent of public transit frequencies, and it can improve riders' health and psychological well-being.[35]

[35] (Cavill and Davis 2007, Daley and Rissel 2011, Oja et al. 2011).

It is difficult to discuss the future of last-mile delivery without addressing the elephant in the room; autonomous delivery vehicles, both flying and land-based. An industry report on the subject even boldly claims that 'Autonomous vehicles, including drones, will deliver close to 100 percent of X2C and 80 percent of all items".[36] It is important to acknowledge that the future of last-mile delivery may very well be dominated by autonomous vehicles. However, we would argue that a future of autonomous vehicles has a) not been delivered yet, and b) will need to overcome some significant hurdles before being fully realized. In the meantime, cargo bikesharing can be an effective method of making last-mile deliveries. Autonomous

[36] (Joerss et al. 2016).

delivery vehicles currently face legal, technological, environmental, and acceptance challenges.[37] All of these can be addressed with the integration of cargo bikesharing into existing e-commerce infrastructure. Bicycles, and bikesharing in particular, have already been addressed in most legal frameworks. Introducing cargo bikes to bikesharing systems will not cause a significant legal headache for most municipalities.

[37] (Aurambout et al. 2019, Hoffmann and Prause 2018, Joerss et al. 2016, Mangiaracina et al. 2019).

Although the technology for a flying drone to carry a package from one point to another exists for the most part, it is not without its limitations. Most notably, these vehicles have an extremely limited parcel capacity and need to be constantly recharged, which reduces the efficiency and cost-effectiveness as a means for last-mile delivery.[38] However, the technology for cargo bikes and bikesharing already exists and has several significant advantages over autonomous delivery vehicles. When compared to other delivery methods, research has shown that utilizing cargo bikes for last-mile delivery can reduce for operations, external, and environmental costs.[39] Additionally, Ignat and Chankov showed that consumers are more likely to choose more sustainable last-mile delivery methods when presented with information about sustainability.[40] If cost-savings are passed on to consumers, they may prefer to pick up parcels with cargo-bikes, even if instant delivery options are available.

[38] (Mangiaracina et al. 2019).

[39] (Arnold et al. 2018, Clausen et al. 2016, Gevaers et al. 2014).

[40] (Ignat and Chankov 2020).

To the best of our knowledge, this chapter is one of few mobility-related studies that includes milieus as social groups in the fairness assessment, and thus also people's root values. This approach helped us understand that not all social groups have equal access to UEI in Munich. UEI primarily serves people with high social status, as other studies with a socioeconomic focus have shown. [41] Using milieus as comparative social groups helped us realize that not all people with high social status are served, but mainly those without traditional orientation. Furthermore, we found that the underprivileged population was also prioritized in the distribution of infrastructure, and the inclusion of parcel lockers and cargo bikesharing can mitigate the exclusion of this population.

[41] (Rai et al. 2020).

This chapter is significant for two reasons. First, the methodology incorporates a diverse range of social groups categorized by social status and ground values into the spatial fairness assessment. Second, the viability and effectiveness of incorporating cargo bikes into bikesharing systems and UEI is explored, which could have significant access and sustainability implications.

In conclusion, e-commerce infrastructure in Munich mainly benefits groups with low social status, and also the cosmopolitan population. If cargo bikesharing were integrated into the system, the distribution of UEI would follow a mix of spatial equity and efficiency criteria. After integration with cargo bikesharing, UEI would serve social groups with the potential to use the system. This scenario could also develop potential benefits such as reducing emissions and space consumption and developing more livable cities. To the best of the authors' knowledge, this is one of the few spatial fairness assessments on e-commerce infrastructure.

Next

The proposed methodology has the advantages of simplicity in calculation and mostly including open-source data and software in the analysis. However, limitations of the study include the use of commercial data for categorizing social groups. Future studies in other cities or regions may use open-source socio-demographic characteristics in their approach for comparison between different social groups to keep a complete "open approach." The method used in this chapter is flexible and can be applied to any socio-demographic breakdown by place of residence.

Stakeholders and policymakers can use similar approaches to make the distribution of resources transparent and gain the trust of users and the public. Access analyses and instruments have been proven to be capable of enabling a discussion between different stakeholders while steering sound policy and decision-making.[42] If spatial distribution criteria do not match their policy or financial preferences, redistribution of parcel lockers and cargo bikesharing infrastructure can be a potential approach to favor those who contribute the most and also those who need the most.

[42] (Büttner et al. 2018, Wulfhorst et al. 2017).

Further research can not only expand on these two points, but also apply the analysis and methodology to other cities, looking at both urban and peripheral areas. Additionally, financial and environmental models can examine the feasibility of the four different scenarios in order to build on and improve these types of analyses. Furthermore, e-commerce allows people to access goods that are not available to them, such as retailers in rural areas.[43] found that in the United Kingdom, the demand for groceries when shopping online is higher in rural areas than in urban areas. Considering these facts, further research can include UEI to

[43] (Kirby-Hawkins et al. 2019).

estimate access to different opportunities that can be purchased online. For example, access to food has traditionally been estimated using access to supermarkets. However, this approach can be extended to include UEI in estimating access to different opportunities that can be purchased online. A theoretical approach would be needed to combine the traditional access analysis with UEI. The four scenarios presented can be used as indicators of access from UEI to destination.

Finally, further research can focus on pricing cargo bikes to include them in delivery costs and incentivize picking up and dropping off goods using a mode of transportation other than a private car. Following the assessment, further implementation of the research findings could be to reorganize bike balance and UEI reallocation strategies to create more equitable urban logistics and shared mobility infrastructure.

10

Spatio-temporal Transit Access to Food Stores

Xiaohuan Zeng, Ying Song, and Na Chen

Abstract: This chapter presents methods and procedures to evaluate the spatial-temporal access to grocery stores considering coupled constraints of transit schedules and store opening hours and investigates the impacts of using different spatial units on analysis results. We use the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) and transit services in Hennepin County, Minnesota as the study case to illustrate our methods and results. We calculate both the primal access and the dual access. We choose network nodes, land-use parcels, and census block groups to examine how the selection of different spatial units affect the analysis. Visualizations of access reveal that the access during early morning and late-night hours is affected the most by the coupled constraints. Most locations toward the suburban areas have less access due to the lack of transit service coverage, and neighborhoods toward the north of Minneapolis have relatively good access only during certain times of the day. Block groups with a relatively higher share of socially disadvantaged groups have a decent number of accessible stores during certain time periods. These findings suggest that decision-makers need to consider the variations in access levels across different spatial locations, times of the day, and social groups within various living-built environments.

Introduction

Access to nutritious and affordable food is crucial to reduce obesity and improve health, especially for low-income communities.[1] In the United States, Special Supplemental Nutrition Program for Women,

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[1] (Breneman 2011, McKinnon et al. 2009).

Infants, and Children (WIC) provide supplemental food, nutrition education, and referrals to health care and other social services to low-income, nutritionally at-risk women, infants, and young children.[2] Existing studies have shown that the WIC program can support healthy and nutritious diets, particularly for pregnant women and preschool children.[3] Studies have also analyzed the attitudes and behaviors of participants of the WIC program and evaluated how well the existing WIC store network serves the participants to promote the program for better services.[4]

Existing studies usually use the distance to grocery stores as the only barriers while evaluating food access.[5] They ignore that low-income people may work long hours or with nonstandard schedules,[6] so they cannot shop at some stores nearby during their opening hours. Most of them often focus on driving as the travel mode. Only a few recent studies address the transit dependency of households without vehicles.[7]

Recent studies integrate time into the measurements of food access.[8] People's spatial access to healthy foods can change over time due to the dynamic presence of farmers' markets, complicating the notion of a static food desert.[9] On the daily scale, travel options,[10], operating hours of food retailers,[11] and changes in public transit schedules[12] can significantly impact access to food. Moreover, access by car and transit can also produce distinct geographies and lead to disparities regarding food access.[13] The spatial unit used for measuring food access has not been fully addressed in the literature. Existing measures still rely heavily on zonal-based geographies such as traffic analysis zones for their simplicity and computational tractability.[14] Land-use modeling in recent years has evolved to incorporate the micro-measure of land use such as land parcels.[15] And recent studies start to investigate how different spatial representations of the population may affect the measured access to food and other resources.[16]

[2] (Oliveira 2009).

[3] e.g., (Hoynes et al. 2011, McGuirt et al. 2018, Rose et al. 1998).

[4] (Davis et al. 2019, Tiehen and Frazão 2016, Treiman et al. 1996).

[5] (Ermagun and Tilahun 2020).

[6] (Hsueh and Yoshikawa 2007, Weston et al. 2003).

[7] (Bostock 2001, Rose and Richards 2004).

[8] (Widener and Shannon 2014).

[9] (Widener et al. 2011).

[10] (Ledoux and Vojnovic 2013, Shannon 2014, Widener et al. 2013).

[11] (Chen and Clark 2013; 2016, Widener et al. 2017).

[12] (Farber et al. 2014, Widener et al. 2015).

[13] (Widener 2017).

[14] (Hunt et al. 2005).

[15] (Waddell 2002).

[16] e.g., (Foti et al. 2012, Langford and Higgs 2006).

Questions

This chapter aims to measure the spatio-temporal access to WIC participating food stores by transit and identify underserved social groups. In particular, it addresses the following questions:

- How do the coupled constraints of transit schedules and store opening hours lead to spatio-temporal dynamics of measured access to WIC participating stores by transit?
- How does the spatial analysis unit affect the measured access and how to mitigate the impacts of using zone-based representations of people?
- Do disparities exist among different social and economic groups regarding the spatio-temporal access to the WIC stores?

Methods

Primal and dual access

To evaluate the access to WIC participating stores by transit, this chapter calculates both primal and dual access during different times of the day.[17] The primal access focuses on the total number of options, and the dual access focuses on the costs of the access. We consider both transit schedules and store opening hours, so a shopping trip from network node N_i to store O_j is feasible during the time of the day $h = [t_n, t_{n+1}]$ if and only if: (1) the trip happens during h, (2) the trip takes less than the budgeted time t_{max}, and (3) the store O_j is open till $(t_{n+1} + t_{shop})$ where t_{shop} is the time for shopping in the store. The node N_i refers to a node in the integrated pedestrian and transit network. Two data sets are used to construct this integrated network. First, the pedestrian network is created using OpenStreetMap (OSM) data, with the speed along edges set as 3 mph. Second, the transit network is created using the General Transit Feed Specification (GTFS) data, with nodes as transit stops and edges connecting two consecutive stops. The travel time between two locations within the integrated network is the sum of the walking time, in-vehicle time, and possible wait time and transfer time.[18]

[17] (Cui and Levinson 2020b).

[18] (Blanchard and Waddell 2017).

We use two Python packages to construct the integrated networks and calculate the travel time within such networks during different times of the day. First, we use the open-source package UrbanAccess to build the integrated network based on the GTFS and OSM pedestrian networks.[19]

[19] (Blanchard and Waddell 2017).

Then, we apply the open-source network analysis package, Pandana, to compute the travel time within the network during a given time as the basis to calculate node access.[20] For primal access,

[20] (Foti et al. 2012).

this chapter applies the Hansen equation.[21] to calculate the primal access of node N_i to stores O_{j_J} during time h:

[21] (Hansen 1959, Levinson and Wu 2020).

$$A_{i,h} = \sum_{j=1}^{n} O_{i,h} f(C_{i,j,h}) \tag{10.1}$$

where,

$A_{i,h}$: primal access of node N_i during time h

$C_{i,j,h}$: minimum travel time from node N_i to store O_j during h

$f(C_{i,j,h})$: function of travel costs subject to the travel time budget t_{max}

$O_{j,h}$: availability of store O_j during h subject to its opening hours $t_{j,open}, t_{j,close}$

This chapter uses the cumulative opportunity measure[22] and employs binary step functions for both $O_{j,h}$ and $f(C_{i,j,h})$ as follows:

[22] See chapter 1 in this volume.

$$O_{j,h} = \begin{cases} 1 & [t_n, t_{n+1} + t_{shop}] \subseteq [t_{j,open}, t_{j,close}] \\ 0 & \text{otherwise} \end{cases} \tag{10.2}$$

$$f(C_{i,j,h}) = \begin{cases} 1 & C_i, j, h \leq t_{max} \\ 0 & C_i, j, h \geq t_{max} \end{cases} \tag{10.3}$$

This means that all accessible stores would have the same unit weight counted toward the primal access of node N_i during time h. Although there is no standard for the desired number of accessible stores, more stores offer more options and hence greater flexibility. Also, there is no standard for the time budget for a shopping trip by transit. This chapter uses 30 minutes as an example of budgeted travel time and also include a 30-minute shopping time, t_{shop}, to ensure that there is enough time to buy needed food after arriving at the store. When survey data becomes available, we can use the collected data to determine the budgeted travel time and shopping time for a typical shopping trip and calibrate the model accordingly.

For dual access, the access of node N_i is calculated as the maximum cost to reach the Ω accessible stores with the lowest costs during h. Analytically, this dual access of node N_i to all stores O_{j_J} during time h is given as:[23]

[23] As developed in (Cui and Levinson 2020b).

$$A'_{i,h} = \max Q_{i,j,h} C_{i,j,h} \tag{10.4}$$

That satisfies

$$\min \sum_{j=1}^{J} O_{j,h} Q_{i,j,h} C_{i,j,h} \tag{10.5}$$

Subject to:

$$\min_{Qh} \sum_{j=1}^{J} O_{j,h} Q_{i,j,h} C_{i,j,h} \tag{10.6}$$

$$\sum_{j=1}^{J} O_{j,h} Q_{i,j,h} \geq \Omega \tag{10.7}$$

$$Q_{i,j,h} \in 0, 1 \tag{10.8}$$

$A'_{i,h}$: dual access of node N_i during time h

Ω: the minimum number of needed opportunities (e.g., 1, 3, 5, ...)

Q_h: incidence matrix at time h with I rows and J columns

$Q_{i,j,h}$: '1' if store O_j is in the set of destinations of node N_i at time h; '0' otherwise

$O_{j,h}$: availability of store O_j during h subject to its opening hours $[t_{j,open}, t_{j,close}]$.

The dual access measures the farthest destination (Equation 10.4) in the set of least-cost destinations (Equation 10.5) that can provide sufficient opportunities (Equation 10.6). Hence, a higher value of $A'_{i,h}$ indicates higher costs and a lower level of access.

To make dual and primal access more comparable, we modify the original dual access measure so that lower dual access indicates a lower level of access. And we also consider the travel time budget t_{max} similar to the primal access:

$$\hat{A}'_{i,h} = minQ_{i,j,h}(t_{max} - C_{i,j,h)} \tag{10.9}$$

That satisfies:

$$max_{Q_h} \sum_{j=1}^{J} O_{j,h} Q_{i,j,h} (t_{max} - C_{i,j,h}) \tag{10.10}$$

Subject to:

$$\sum_{j=1}^{J} O_{j,h} Q_{i,j,h} \tag{10.11}$$

$$C_{i,j,h} \leq t_{max} \tag{10.12}$$

$$Q_{i,j,h} \in 0, 1 \tag{10.13}$$

The modified dual access, therefore, measures the minimum extra time left after the trip given the budgeted time (or other cost budgets). This chapter considers accessing at least one WIC store Ω as an example. If survey data becomes available, the parameters, Ω, Q_h, and t_{max} can be calibrated based on the preferred number of accessible stores, the specific nutrition needs (e.g., gluten-free), and the budgeted time for shopping trips.

To examine the variation of spatio-temporal access to WIC stores, we visually compare the primal and dual access across the study area and identify potential spatial disparities. We compare the access throughout the day to investigate how the coupled constraint of store opening hours and transit schedules affects the identified disparities.

Access by spatial units

This chapter continues to investigate how the choice of spatial units may affect the access measures. We calculate the primal and dual access at the level of network nodes, land-use parcels, and census block groups. First, we use the nodes of the integrated networks as the finest level considering that people's movements are often restricted by transport networks. We use land-use parcels as the second level because the parcel is the basic unit for residential housing and apartments, and office buildings, and we can distinguish residential, commercial, and other land-use types and treat them differently. Third, we use census block groups for zonal aggregation because it is a proxy for neighborhoods and most demographic and economic data are available at this level in the US.

To get the WIC store access based on these three spatial units, we first calculate the primal access and dual access of network nodes hourly. The time range is consistent with the service period of a given day in the input GTFS data. And including a period from midnight to 5:00 AM the following day can also account for the possible shopping trips occurring around midnight.

Given the calculated primal and dual access at the network node level, we derive the access at the parcel level. We first select residential and apartment parcels and then spatially join each parcel P_k to its nearest network node N_k. We then assign the primal and

dual access of parcel P_k as the same as its nearest node N_k, considering that the integrated network by these residential and apartment parcels is always at the block level and can often be reached in less than a minute. Finally, we obtain the access for a census block group as the average of the access of all residential and apartment parcels within that census block. When calculating the average access, all parcels within a block group are considered, not just only those that have positive primal or dual access. We also calculate the standard deviation of parcels' access level and the ratio of parcels without access to WIC stores, which can represent the intra-zone variations inside aggregated units.

Access by social groups

Besides describing the disparity in primal and dual access from the spatial and temporal perspectives, this chapter further investigates the correlates of these two access measures at the block group level through visual comparisons and regular ordinary least squares (OLS) regression analysis. We select major independent variables for socioeconomics and built environments. The socio-economic variables are selected with a focus on social equity, such as the shares of families below poverty level and females at childbearing age. The built environment is specified as transit stop density, shares of different land-use types, densities of employment and population, and the regional access in terms of distance to the nearest city center.

Study area and data

This chapter uses WIC eligible stores, pedestrian network and transit systems in Hennepin County, Minnesota, US as an example case to demonstrate the methods and results. The three sets of data used in this chapter correspond to the three key components of access measures, that is, the origins, the destinations, and costs (in travel time).

The first data set contains WIC-approved grocery stores as the trip destinations. The list of these WIC stores in Minnesota is available at the official website of the Minnesota Department of Health. The original data set only lists the name and address of each store and does not contain store opening hours. Hence, this chapter first collects the WIC stores' geographic coordinates and opening hours using the Google Maps Place API. The final data set

contains 832 stores participating in the WIC program in Minnesota, and among them, 177 WIC stores are within Hennepin County, including chain retailers like Target as well as small local stores.

The second data set contains the integrated transport network. We use the GTFS data in the Twin Cities metropolitan areas on Tuesday, August 21st, 2018 as an example transit schedule on a weekday and build the transit network. The GTFS data contains 13,099 stops and 47,685 trips along 185 routes. And we retrieve the pedestrian networks from OSM, which contain 199,023 nodes and 584,165 edges. The integrated network is used to calculate the travel time by transit from network nodes to WIC stores during time h. And the network nodes are also used as trip origins at the finest spatial level.

The third data set contains the selected and calculated social demographics and the built environmental information at the census block group level. For the social demographic characteristics, we consider gender, age, income, poverty level, vehicle ownership, public support, and education attainment.[24] The data we use to calculate the built-environmental variables include the spatial locations of Minneapolis and St. Paul city centers, transit stops, land-use parcels, street intersections, and densities of population and employment. The census related data is retrieved from the National Historical Geographic Information System (NHGIS)[25] and the Longitudinal Employer-Household Dynamics (LEHD).[26] The land-use parcel data is retrieved via the Minnesota Geospatial Commons, which contains parcels in 7 metro counties in 2018.

[24] (Jiao and Dillivan 2013, Trippe et al. 2019).

[25] (Manson et al. 2017).

[26] (US Census Bureau 2020a).

Figure 10.1 shows the spatial distribution of population, transit stops, WIC stores, and land-use types in the study area. In general, areas with higher population density have more transit stops, and areas with larger shares of commercial parcels have more WIC stores.

Figure 10.1 also reveals that there are a few WIC stores available toward the north but few transit stops are located there, and there are no WIC stores toward the west side.

Findings

Primal and dual access

First, we investigate the dynamics of primal and dual access at the network node level for the entire study area. Figure 10.2 uses the boxplots to present the access of all nodes hourly from [01:00 AM,

02:00 AM] to [04:00 AM, 05:00 AM] of the next day. We use Tuesday, Aug. 21$^{\text{th}}$, 2018 as an example weekday to demonstrate the results. The lower and upper bounds of each box correspond to Q1 and Q3 quantile values of the data respectively, that is, there are 25% values below the lower bound and 75% of values below the upper bound. The line and white circles in the middle of the box indicate the median (Q2) and average access respectively. Each whisker presents the range of the data, and it extends no more than 1.5×(Q3-Q1) from the box to exclude outliers.

Overall, both primal and dual access increases quickly in the early morning and drop quickly from the early night. For primal access, these changes occur from 5:00 AM to 10:00 AM in the morning and from 6:00 PM to 12:00 PM at night. For dual access, these changes occur a little earlier from 3:00 AM to 8:00 AM and similarly from 6:00 PM to 12:00 AM. This is because the primal access considers all stores that are accessible within 30 minutes while the dual access only considers the nearest accessible stores. Since most stores are not open until 8:00 AM, the primal access continues to increase from 8:00 AM as more and more stores start to open while the dual access starts to decrease from 8:00 AM due to the less frequent transit service after morning peak hours. In addition, despite that both mean and median dual access remain high from 7:00 AM to 7:00 PM, the variation during the middle of the day from 9:00 AM to 3:00 PM is larger and more nodes with low access level (Q1 to Q2). Such reduction in access is following the less frequent transit services during off-peak hours. These findings suggest that the coupled constraints of transit service and store opening hours have great impacts on both the primal and dual access, but such impacts are slightly different between them.

To further investigate how the coupled constraints can spatially affect the dynamics of primal and dual access, we select the time intervals from 6:00 PM to 12:00 AM at night and visualize the access at the network node level. Figure 10.3 shows the primal access at nodes; the darker green indicates more accessible WIC stores from the nodes and therefore higher primal access. Figure 10.3 suggests that downtown Minneapolis has the highest access across the study area. Figure 10.3c and Figure 10.3d indicate a significant drop in the center toward the eastern areas where there are transit stops nearby and most of them are no longer in service after 10:00 PM (see Figure 10.1a for stop distribution). Figure 10.3d and Figure 10.3d show a significant drop toward the north of downtown Minneapolis

which locates many WIC stores and most of them close after 10:00 PM (see Figure 10.1b for store distribution).

Similarly, Figure 10.4 shows the dual access at the network node level. We use 10, 15, 20, 25, and 30 minutes as the break values and darker colors indicate more time left after the trip and higher access thereafter. We have similar findings: the area from the center of the study area toward the eastern has a sudden drop in access from 9:00 PM to 11:00 PM and the area toward the north of downtown Minneapolis has a sudden drop in access from 10:00 PM to 12:00 PM. This is most likely due to the reduction in transit service around these areas after 9:00 PM. In sum, findings from primal and dual access both suggest that the coupled constraints have greater impacts on some areas than others and that north Minneapolis experiences the greatest impacts. These findings also suggest that areas with more transit stops or WIC stores may have higher access than other areas, but such advantages are likely to only exist during specific periods

Spatial analysis units

We continue to examine the impacts of aggregating primal and dual access measured at the network node level to zonal levels, which include land-use parcels and census block groups. We use the primal and dual access from 6:00 PM to 7:00 PM as an example to visually explore the impacts. The spatial patterns are preserved well in general (see Figure 10.5 and Figure 10.6). The parcel-level results in Figure 10.5b and Figure 10.6b appear to be similar to the node-level results in Figure 10.5a and Figure 10.6a, but it can exclude commercial and industrial parcels and therefore highlight the patterns for residential parcels. For future studies that focus on non-home-based shopping trips (e.g., shopping trips from work), we can choose other parcel types and answer specific research questions of interest. For the census block group, both Figure 10.5c and Figure 10.6c indicate the loss of intra-zone variations regarding access. For instance, there are only a few nodes with high access from the center toward the west of Hennepin county while most nodes in those areas have relatively low access. When we aggregate the access from the node level to the census block group level, the census block groups in those areas have a medium level of access and the variations of access within each block group can not be shown.

To further examine the intra-zone variation, we calculate the standard deviation of parcels' primal access within each census block group hourly from 6:00 PM to 12:00 AM. As shown in Figure 10.7, we can observe smaller variations in downtown Minneapolis and toward the edge of Hennepin county. And as time goes, such differences become less significant overall. Areas in the transition areas from downtown to suburb have relatively higher variations before 11:00 PM, and from 11:00 PM to 12:00 AM, we can observe a sudden decrease toward the north of downtown Minneapolis, which is consistent with the findings at the node level (see Figure 10.3e and Figure 10.3f). This suggests that aggregating results at the parcel level can preserve the spatial patterns pretty well in general.

For dual access, we use the ratio of parcels that do not have any extra time left from the budgeted time after the shopping trip to the nearest store. This can reveal potential information lost while aggregating access from parcels to block groups. As shown in Figure 10.8 more than 80% of the parcels in the block group toward the west of Hennepin county cannot access any WIC store within 30 minutes. However, when we aggregate the dual access to the block group level, those areas are shown as having relatively lower dual access and the intra-zone variation gets lost (see Figure 10.6c). Similar to the primal access, the intra-zone variations become less obvious towards later night, especially after 11:00 PM. Unlike the primal access, variations near downtown Minneapolis are the least due to relatively higher dual access of all parcels in the area. These findings suggest that the intra-zone variations cannot be preserved well while aggregating the dual access from the parcel level to the block group level. Therefore, it is necessary to consider the intra-zone variation while evaluating the access using larger zones like census block groups.

Social groups and built environment

We first explore the spatio-temporal variation of WIC store access and demographics visually through mapping with a focus on the population and households who may be qualified for the WIC program and rely on transit for shopping. Figure 10.9a and Figure 10.9b show changes in the primal and dual access if the trip happens during [10:00 PM, 12:00 AM] compared to [8:00 PM, 10:00 PM]. Overall, both primal and dual access decreases due to the

decrease in transit services and opening stores. This means people have fewer options and need more time for transit trips. The access in some areas is more sensitive to the time of the day than others, which means that these areas only have good access to the WIC stores during specific times of the day (see lighter green polygons in Figure 10.9a and darker red polygons in Figure 10.9b). It shows that north Minneapolis is impacted the most by this temporal restriction. To further identify who may be most affected, Figure 10.9c to Figure 10.9f present selected population and household characters and indicators of their built environment. It appears that those northern areas have relatively higher ratios of the population under the poverty line, families with cash support, and housing units with no vehicles. This suggests that people who may rely on transit services to shop at WIC stores have to make such transit trips during very limited time windows.

In addition to the visual exploration and comparison, this chapter further explores some key correlates of primal and dual access via OLS regression modeling to better understand the access disparity among different social groups within various living environments. The models estimate primal and dual access of block groups during three time periods (6:00 PM to 8:00 PM, 8:00 PM to 10:00 PM, 10:00 PM to 12:00 AM) with two groups of correlates including socio-economic characteristics and built-environmental features.

The selection of the socio-economic variables in the model concerns social inequality in food access for some specific social groups based on correlation analysis. Table 10.1 presents the descriptive statistics of correlates used in the OLS models. It shows that the mean primal and dual access for all block groups drop significantly as time goes and so does their variation. Despite the relatively high density of residential parcels, the land-uses are diverse in Hennepin county. The population and jobs are not evenly distributed as well given the high variance (standard deviation). For the socio-economic profile, housing units with no vehicle are 9.42% on average, but the standard deviation is 12.49% which suggests those non-vehicle housing units may be located in a few block groups. This pattern is also seen for families below the poverty level with kids 5 years old or younger and non-white population. These findings are consistent with visual explorations in Figure 10.9.

The modeling results are presented in Table 10.2 and Table 10.3. For primal access, people in census block groups with higher shares

of no-vehicle housing units and females at childbearing age, and with more households receiving public assistance have more accessible WIC stores consistently across the first two time periods (6:00 PM to 8:00 PM and 8:00 PM to 10:00 PM). These findings reveal that people residing in neighborhoods with more socially disadvantaged groups do not necessarily suffer from low WIC access measured as primal access in this chapter. However, the result in education and race is not consistent with these findings as block groups with lower education levels and more non-whites have lower primal access to WIC stores by transit from 10:00 PM to 12:00 AM. Such results point out the importance of evaluating social inequality regarding food access from different perspectives of grouping people. This chapter evaluates the impact of the built environment on access through the measurements of bus stop density, proportions of different land-use types, distance from the block group to the nearest city center, densities of population, street intersection, and employment (only included in dual access models). The significant modeling results suggest that an urban neighborhood designed with compact urban patterns along with more transit service is likely to offer people with better primal access by transit.

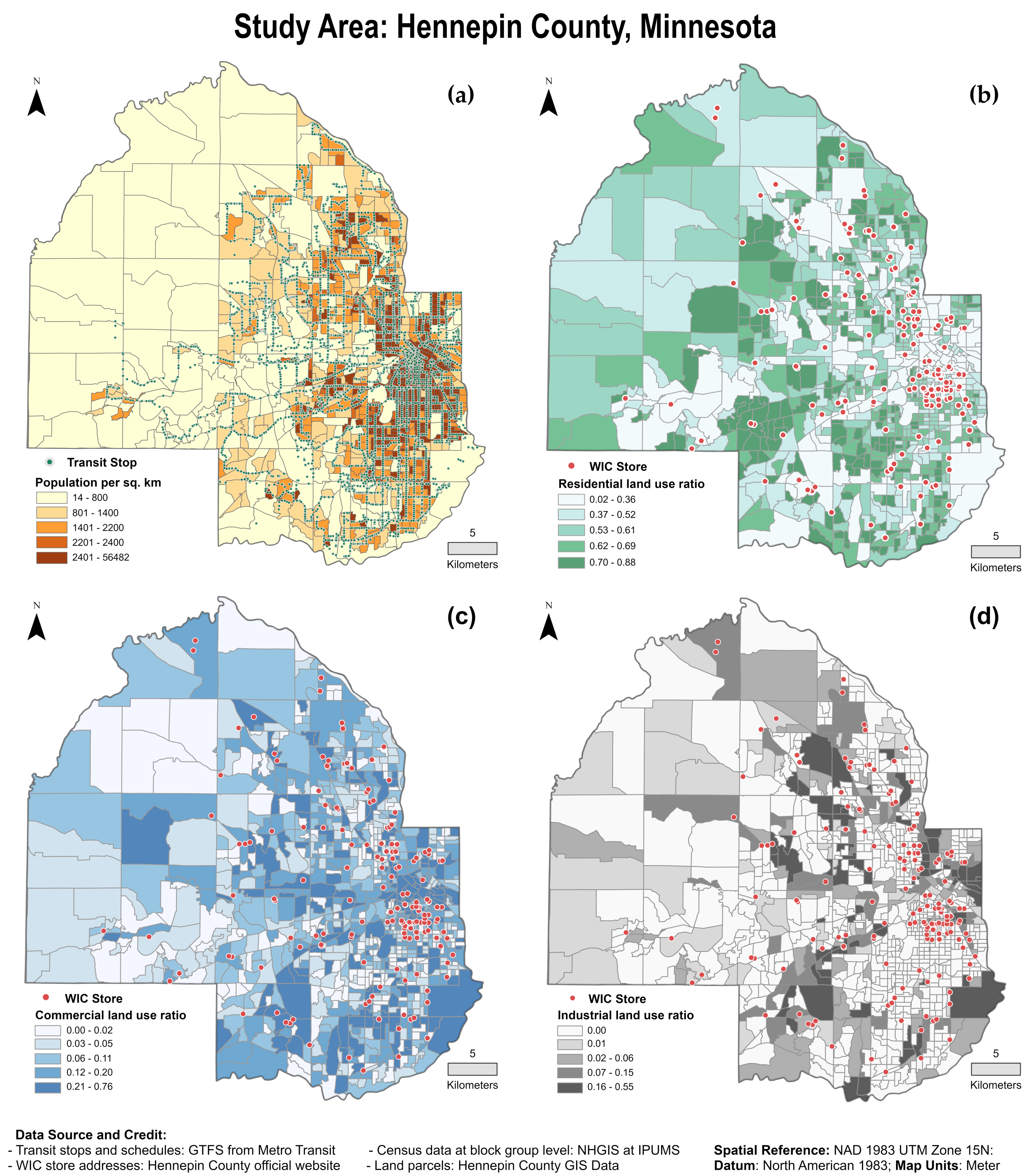


Figure 10.1: Overview of the study area: Hennepin County, Minnesota, US

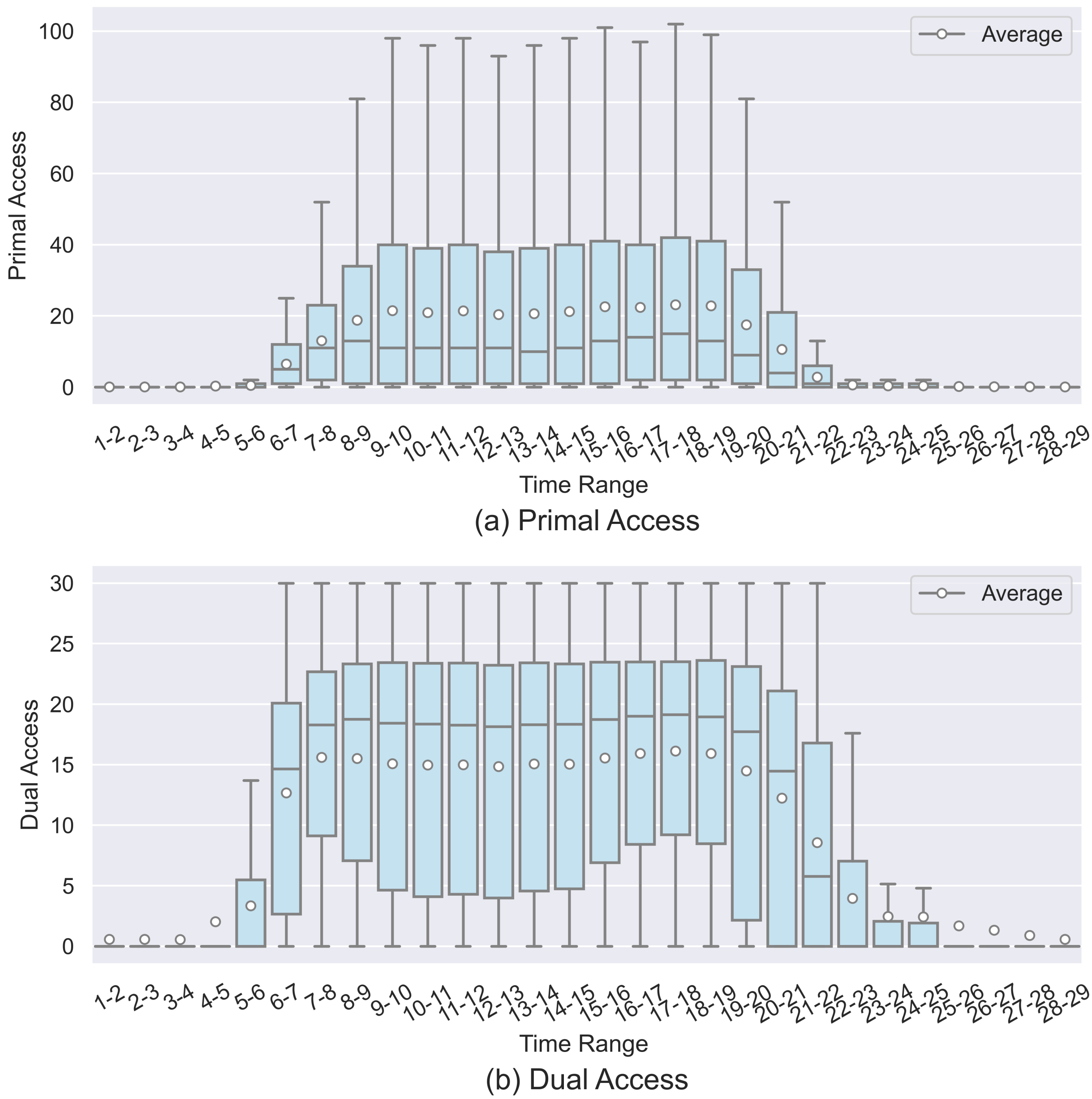


Figure 10.2: Primal and dual access of network nodes across different times of a day

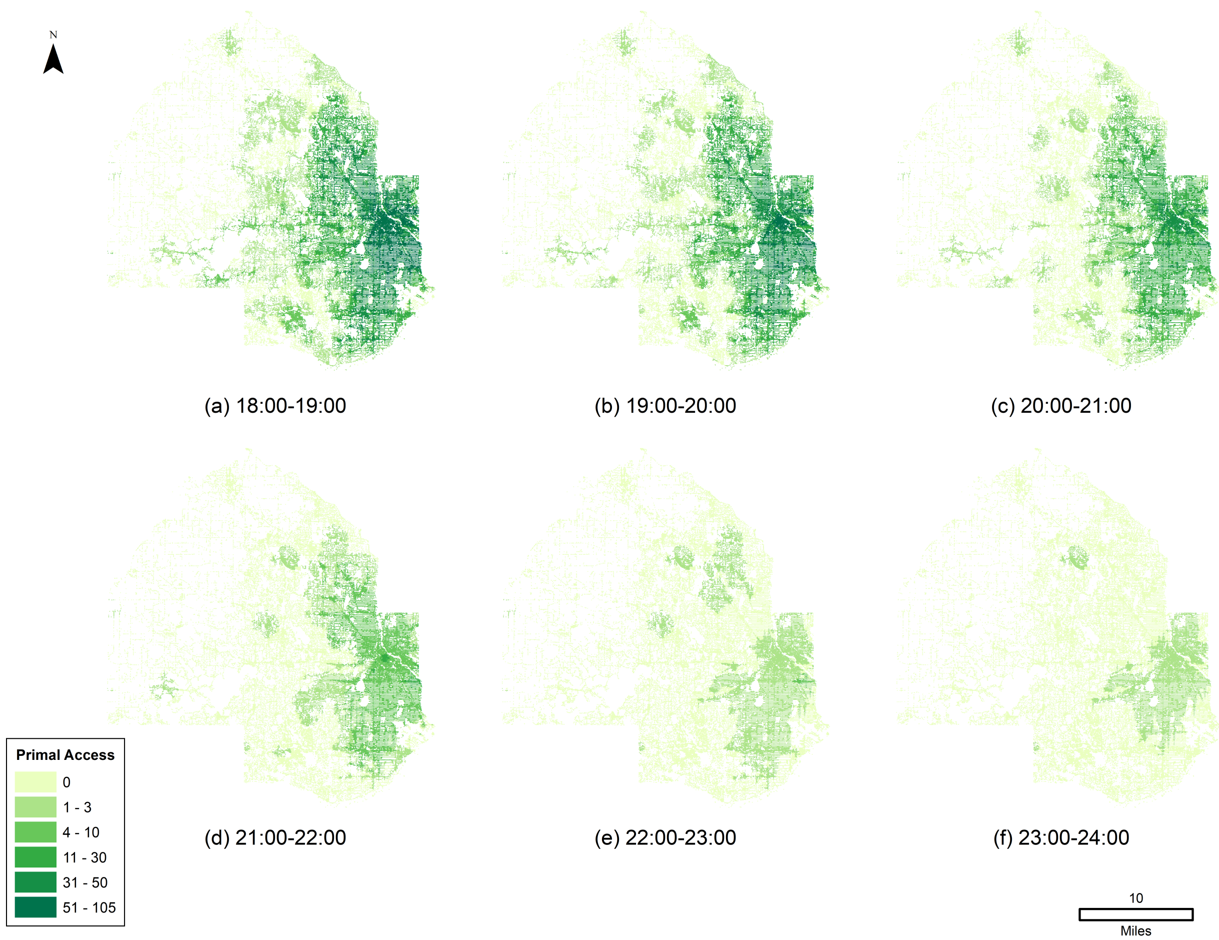


Figure 10.3: Spatial variations of primal access dynamics at the network node level

Figure 10.4: Spatial variations of dual access at the network node level

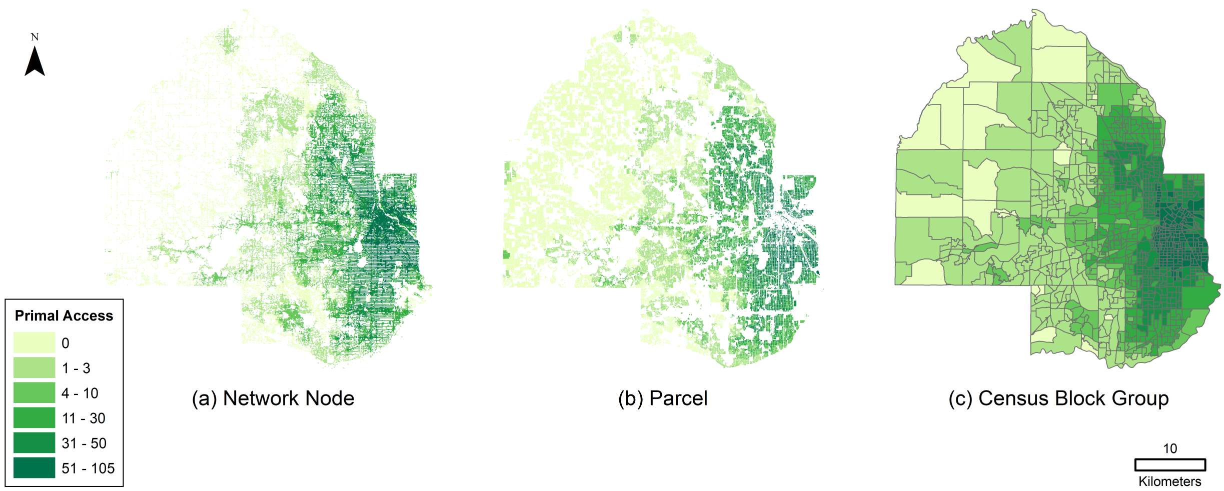


Figure 10.5: Primal access at three different spatial levels from 6:00 PM to 7:00 PM

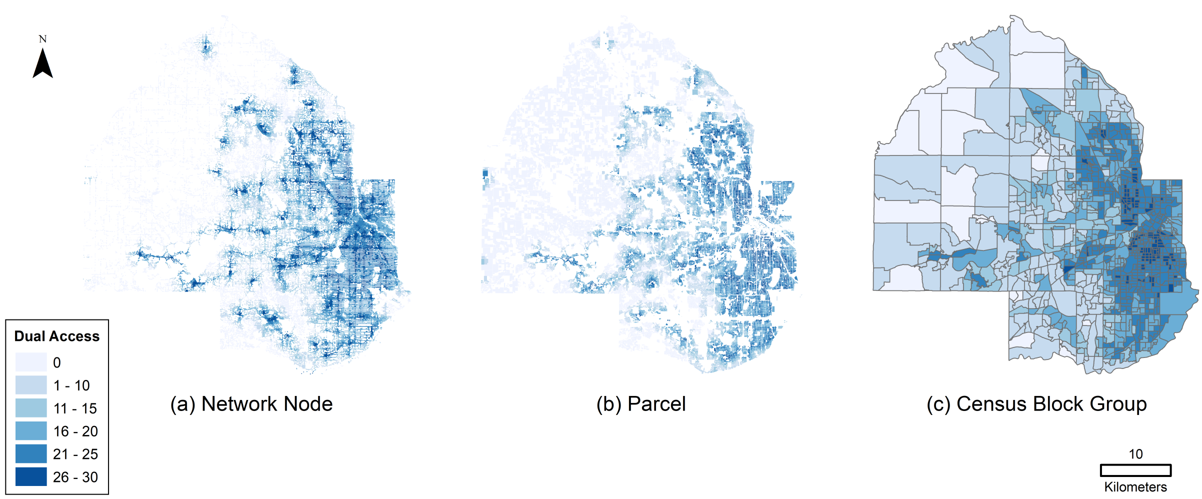


Figure 10.6: Dual access at three different spatial levels from 6:00 PM to 7:00 PM

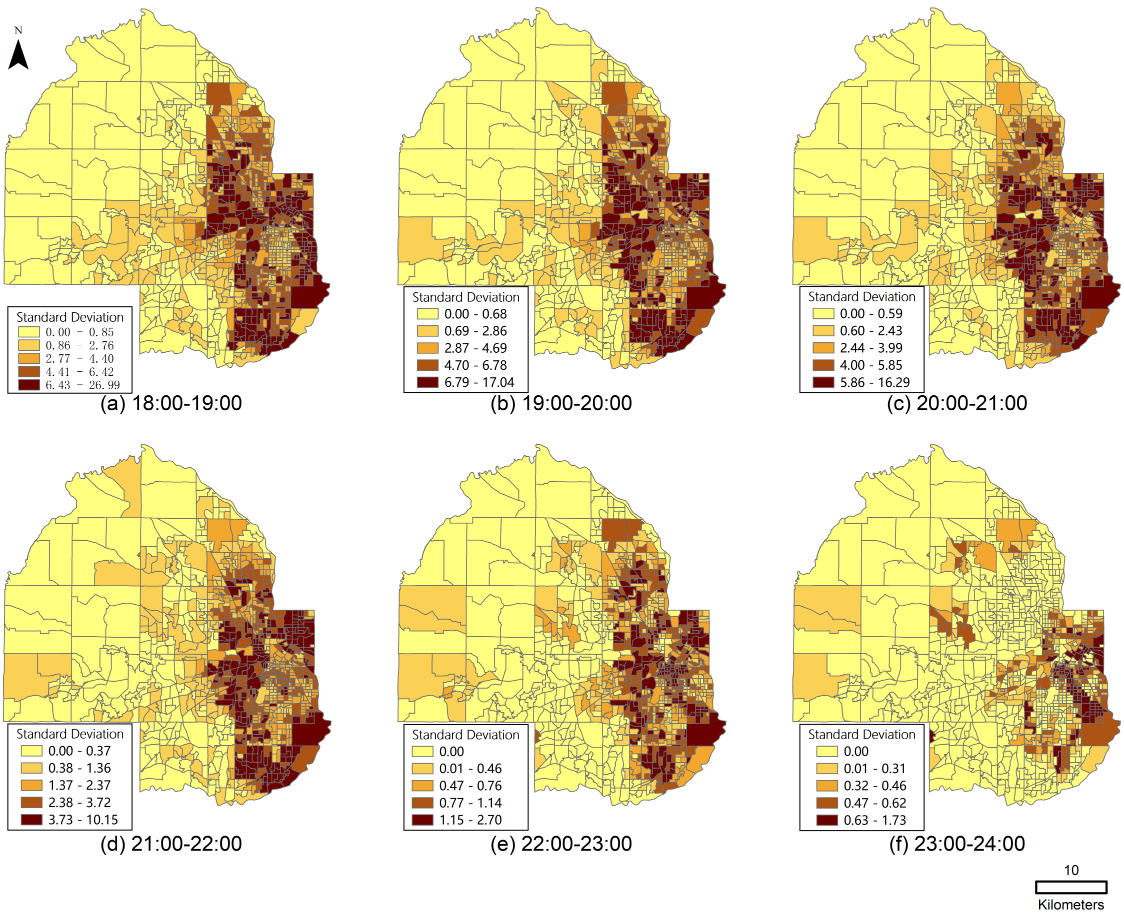


Figure 10.7: Standard deviations of parcels' primal access within census block groups

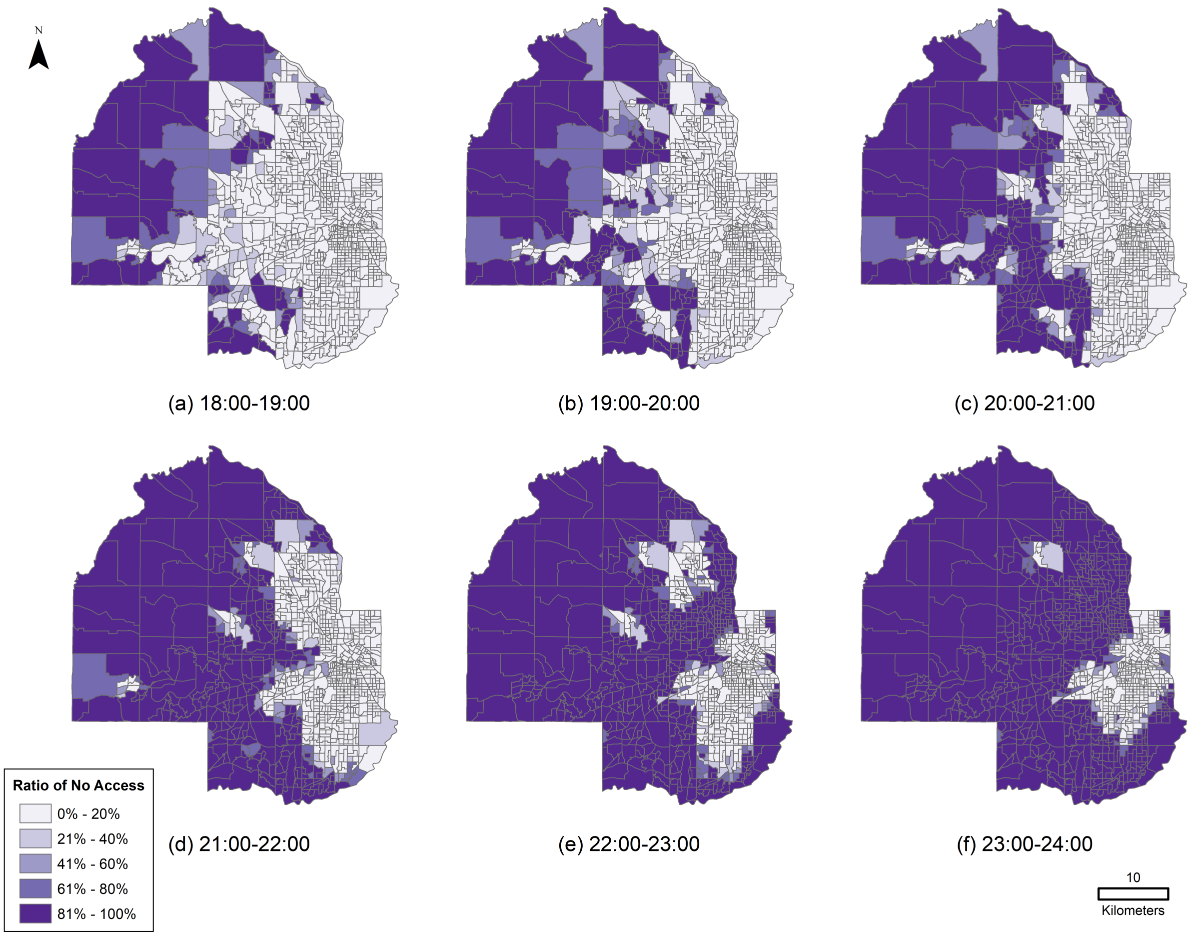


Figure 10.8: Ratios of parcels with no store accessible in 30 minutes in each block group

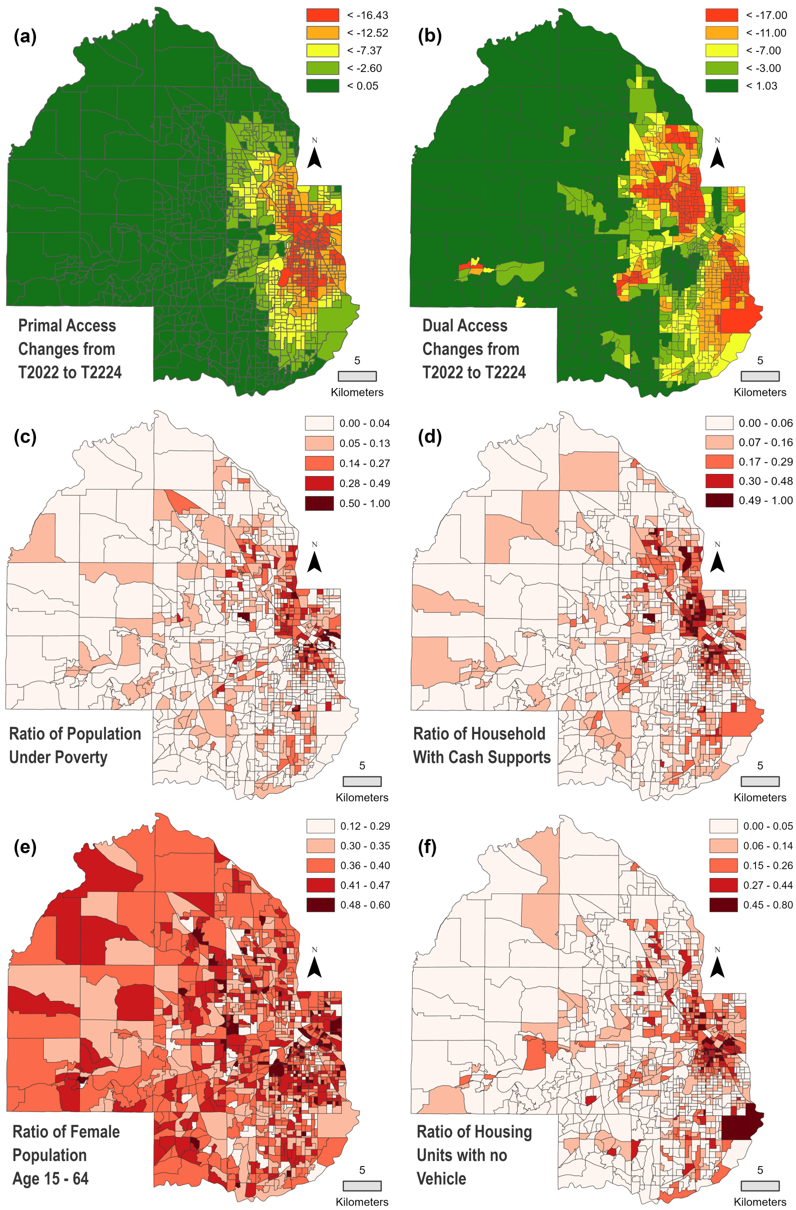


Figure 10.9: Changes in primal and dual access relating to social demographics

Variable	Definition (Unit: Block Group)	Mean	S.D
Primal Access (6:00 PM - 8:00 PM)	Number of accessible stores within 30 minutes by transit from 6:00 PM - 8:00 PM	24.42	19.94
Primal Access (8:00 PM - 10:00 PM)	Number of accessible stores within 30 minutes by transit from 8:00 PM - 10:00 PM	8.39	7.38
Primal Access (10:00 PM - 12:00 AM)	Number of accessible stores within 30 minutes by transit from 10:00 PM - 12:00 AM	0.55	0.63
Dual Access (6:00 PM - 8:00 PM)	Extra time left after transit trip given 30 minutes budgeted time from 6:00 PM to 8:00 PM	16.71	8.15
Dual Access (8:00 PM - 10:00 PM)	Extra time left after transit trip given 30 minutes budgeted time from 8:00 PM to 10:00 PM	12.54	8.50
Dual Access (10:00 PM - 12:00 AM)	Extra time left after transit trip given 30 minutes budgeted time from 10:00 PM to 12:00 AM	4.09	5.69
Built Environment			
% of commercial parcels	% of land that are commercial parcels	11.47	12.20
% of industrial parcels	% of land that are industrial parcels	2.96	7.91
% of residential parcels	% of land that are residential parcels	52.69	18.45
Distance to the nearest city center	Distance in kilometers to the nearest city center (Minneapolis or St. Paul)	10.68	6.80
Employment density	Number of jobs per sq. kilometer	1229.05	4556.50
Population density	Number of persons per sq. kilometer	2429.80	2860.14
Street Intersection density	Number of street intersection per sq. kilometer	56.55	31.66
Socio-Economic Characteristics			
% of low-income families with young kid	% of families below the poverty level with kids 5 years old or younger	1.23	5.23
% of housing units without vehicles	% of housing units that have zero vehicle	9.42	12.49
% of females from 15 to 64 years old	% of females from 15 to 64 years old (childbearing age)	33.80	5.92
% of the population with at least bachelor's degree	% of population with bachelor or higher degrees	47.84	20.14
% of households with public assistance	% of households that receive public assistance	24.63	10.42
% of non-white population	% of population who are not white	26.37	22.58

Table 10.1: Descriptive statistics of variables

Variable	Primal Access (6:00-8:00 PM)		Primal Access (8:00-10:00 PM)		Primal Access (10:00 PM-12:00 AM)	
	Coef.	t -value	Coef.	t -value	Coef.	t -value
Socio-Economic Characteristics						
% of housing units without vehicles	0.071	1.85	0.026	1.86	0.002	1.00
% of females from 15 to 64 years old	0.181	3.07 **	0.070	3.29 ***	0.003	1.01
% of population with at least bachelor's degree	-0.047	-1.97 *	-0.013	-1.54	0.005	4.72 ***
% of households with public assistance	0.115	2.82 **	0.035	2.38 *	-0.001	-0.38
% of non-white population	-0.025	-1.11	0.000	0.02	-0.002	-1.93
Built Environment						
Bus stop density	0.134	10.04 ***	0.045	9.35 ***	0.004	6.68 ***
% of commercial parcels	-0.179	-4.62 ***	-0.081	-5.77 ***	-0.0002	-0.13
% of industrial parcels	-0.251	-4.87 ***	-0.113	-6.07 ***	-0.001	-0.26
% of residential parcels	-0.177	-6.04 ***	-0.076	-7.18 ***	-0.003	-2.44 *
Distance to the nearest city center	-2.842	-26.74 ***	-1.052	-27.37 ***	-0.061	-12.52 ***
Population density	0.0003	5.34 ***	0.0001	5.62 ***	0.00001	3.80 ***
Street Intersection density	-0.0039	-0.80	0.0001	0.06	0.00037	1.67
Constant	42.414	11.51		15.389	11.54	
Model Statistics						
Adj. R^2	0.722		0.734		0.422	
No. of observations						973

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 10.2: OLS modeling results for primal access

Regarding dual access specified as the travel time in terms of extra time in minutes left after traveling to the closest WIC store given the budgeted time (30 minutes) during the same periods mentioned above, there are some interesting findings over the same groups of correlates as shown in Table 10.3. Among the socioeconomic variables, the share of families below the poverty level with kids who are 5 years old or younger shows a slightly significantly negative impact on dual access by transit from 8:00 PM to 10:00 PM. In other words, people from the areas with more poor families need more time by transit to access the nearest WIC stores from 8:00 PM to 10:00 PM. Interestingly, people living in neighborhoods with more well-educated residents travel longer to gain WIC resources during early nighttime, but this relationship turns negative after 10:00 PM. The significant and positive relationship between dual access and the share of households with public assistance is found during the first two time periods, implying a lack of inequality in accessing WIC stores for this specific social group from a travel time perspective, especially from 6:00 PM to 10:00 PM. These findings of the built-environmental variables in the models for dual access are mostly consistent with the ones in the primal access models, except for relatively fewer significant variables and the opposite impact of street intersection density during late night. Overall, those significant findings report that a populated neighborhood equipped with more transit services, fewer commercial and industrial parcels (particularly for the access from 8:00 PM to 10:00 PM) and jobs, and being closer to a city center could provide greater access in terms of requiring less time to reach the nearest WIC store by transit.

Variable	Primal Access (6:00-8:00 PM)			Primal Access (8:00-10:00 PM)			Primal Access (10:00 PM-12:00 AM)		
	Coef.	t -value		Coef.	t -value		Coef.	t -value	
Socio-Economic Characteristics									
% of low-income families with young kids	-0.017	-0.53		-0.059	-1.85		-0.016	-0.54	
% of housing units without vehicles	-0.024	-1.32		-0.009	-0.51		0.059	3.60	***
% of females from 15 to 64 years old	-0.005	-0.17		0.061	2.23	*	0.087	3.50	***
% of population with at least bachelor's degree	-0.071	-6.41	***	-0.075	-6.79	***	0.042	4.14	***
% of household with public assistance	0.082	4.35	***	0.091	4.81	***	0.014	0.81	
% of non-white population	0.009	0.83		0.021	2.04	*	-0.038	-4.01	***
Built Environment									
Bus stop density	0.061	9.16	***	0.053	7.91	***	0.043	6.97	***
% of commercial parcels	0.011	0.63		-0.040	-2.19	*	0.010	0.63	
% of industrial parcels	-0.060	-2.52	*	-0.062	-2.62	**	-0.008	-0.39	
% of residential parcels	-0.012	-0.91		-0.026	-1.92		-0.008	-0.66	
Distance to the nearest city center	-1.098	-22.27	***	-1.191	-24.18	***	-0.437	-9.70	***
Employment density	-0.0001	-4.58	***	-0.0001	-4.23	***	-0.00003	-2.37	*
Population density	0.0001	1.81		0.0001	2.68	**	0.00015	5.97	***
Street Intersection density	0.001	0.46		-0.003	-1.23		-0.004	-1.74	
Constant	23.763	13.96	***	19.560	11.51	***	0.659	0.42	
Model Statistics									
Adj. R^2	0.645			0.674			0.395		
No. of observations									973

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 10.3: OLS modeling results for dual access

Conclusions

This chapter has presented how to evaluate the spatio-temporal access to food by walking and transit considering the coupled constraints of transit schedules and store opening hours. This chapter has considered both primal access (the number of accessible stores within a time budget) and dual access (the time required to access a given number of opportunities). Using WIC participating stores in Hennepin County, Minnesota, US as an example, this chapter has found that the coupled constraints result in obvious temporal patterns of both primal and dual access in the study area, and the changes in access across time are quite different across spatial locations or regions. Before aggregating the primal and dual access to the census block groups and relating to population profiles, this chapter has discussed the choices of spatial units on the evaluations of access and suggested including intra-zone variations as part of the access measures. Finally, this chapter has related the measured access with selected social demographic and built environment variables. The modeling results have showed that while people living in a neighborhood with a relatively high share of socially disadvantaged groups (e.g., families with zero vehicle ownership) are not limited by their primal access through transit, they do need more time to access the nearest WIC stores. Interestingly, results on primal and dual access both have suggested that people living in a populated urban neighborhood with shorter distance to city centers and more transit services have higher access to WIC stores by transit in general. Another important information obtained from these models is the varying impacts of correlates on the same access within different time periods, implying the importance of avoiding adopting one single access value to evaluate transport and spatial inequality.

Next

The visual explorations of spatio-temporal access to WIC stores and the statistical modeling results suggest that decision-makers would need to consider the variations in access levels across different spatial locations, times of a day, and social groups within various living built environments. For instance, neighborhoods in Twin Cities metro areas with relatively higher shares of socially disadvantaged groups can access a decent number of stores within

the time budget (e.g., 30 minutes), but they need more time to access the nearest one, especially when transit services and opening stores become less available during late night. Findings like this suggest that considering all spatial, temporal, and social dimensions is essential to provide comprehensive evaluations of access and avoid any hidden issues regarding food access.

Identifying spatio-temporal variations in food access can help decision-makers develop more effective and equal land-use and transport strategies to minimize the inequalities in the access to nutritious and affordable food and therefore improve public health, especially for those socially disadvantaged groups. Although this chapter uses WIC stores and transit services in the Twin Cities as a study case, the same analytical methods and visualization techniques could be applied to other types of food outlets providers as well as other study regions.

11
Multi-destination Access

Andrew Guthrie and Yingling Fan

Abstract:
This chapter explores the ability of transit systems in regions to provide access to multiple, mutually important destinations for marginalized workers. In six fast- and slow-growing US regions with varying levels of fixed-guideway transit investment, we measure and map access in terms of binary access to regional employment centers and higher education institutions and workforce service providers from areas of concentrated poverty. We employ a binary logistic regression model to explain the probability of a block group having access to all three destination types as a function of transit system characteristics, location in the city, and demographic characteristics. In both slow- and fast-growing regions, areas of concentrated poverty near fixed-guideway transit stations are significantly more likely to have access to all three destination types than areas of concentrated poverty without fixed-guideway transit access. Dividing proximity to rail stations into bands of distance at 400, 800 and 1,600 meters (0.25, 0.5 and 1 mile), we find roughly a seven-fold increase in the probability of a block group having access to all three destination types with each band closer to a rail station. The results provide compelling evidence for the social equity benefits of regional transit investments, as well as for the importance of integrated transit, land use, and regional public service planning.

Introduction

Keywords: Public transport; Access to education; Spatial mismatch

Rail transit implementation represents a large investment of public funds frequently justified at least in part on the basis of providing region-wide access to a diverse range of destinations. Access analysis measures the degree to which a transport system provides access to desired destinations, however, a traditional focus on

measuring access to one type of destinations – jobs – calls for new analysis approaches to gauge the success of fixed-guideway transit investments in providing access to multiple destination types even in fully considering the employment implications of transit. For example, access to living wage work is unhelpful absent access to the education needed to obtain required qualifications. In this chapter, we broaden measurement of employment-focused access by considering access to jobs themselves, higher education and job centers. Cumulative opportunity measures[1] offer a powerful measure of transport system performance by directly measuring what it is possible for users to achieve by traveling.[2] As such, it provides more practical information than simple mobility measures and fits with established theoretical understandings of transport as a derived demand. We travel to reach places, not for the sake of moving through space in and of itself.

In practice, cumulative opportunities measures require researchers to consider access to a specified type of destinations.[3] For one thing, a comprehensive count of all places one might care to visit is difficult, if not impossible, to obtain at a systematic, regional scale; for another, destinations are not equally valuable to all users. As a result, most existing access analyses measure access to jobs, due both to the importance of access to employment in determining users' life outcomes and to the fact that most regularly visited, non-home destinations have some level of employment associated with them, allowing jobs to function as an approximation of activity in general.[4]

In reality, of course, people need access to other destinations besides jobs.[5] This is especially the case with regard to generationally poor and/or long-term unemployed workers, who often require access to education, training and job search services to expand the number of jobs they are qualified for.[6] For example, access to workforce development service centers significantly reduces length of unemployment, especially for particularly disadvantaged groups such as single mothers.[7] As a result, for a significant number of disadvantaged individuals, we can conceptualize access to opportunity for bettering one's lot in life as access to employment and education and workforce development services. Measuring access to opportunity from this perspective requires a different approach than the simple count of jobs reachable common in the cumulative opportunities measures.

[1] See chapter 1 in this volume.

[2] (Levinson and Krizek 2005, Owen and Levinson 2015).

[3] Cui and Levinson (2020a) is a noticeable recent exception, and uses a dual measure of access.

[4] (Fan et al. 2012, Guthrie and Fan 2016).

[5] (Ermagun and Tilahun 2020, Fan et al. 2012, Grengs 2015).

[6] (Guthrie et al. 2018).

[7] (Joassart-Marcelli and Giordano 2006, Weber 2003).

Attempts to improve employment outcomes via improved transport access seek to remedy the long-standing problem of spatial mismatch – a lack of alignment between jobs disadvantaged workers are qualified for and transport systems they are able to access.[8] Though a significant obstacle to social mobility, spatial mismatch as traditionally defined is not the only transport-related obstacle to social mobility.[9] Skills mismatch, by contrast, describes a lack of alignment between entry-level jobs disadvantaged workers are able to reach with the transport modes available to them and jobs for which they are qualified.[10] Of course, in practice both these types often coexist, and both can be partly addressed through transport policy – spatial mismatch via improved access to jobs, skills mismatch through improved access to education and workforce services.[11] In addition, access to major employment centers in particular plays an important role in access to jobs and other types of activity as well.[12] Regional employment centers play a prominent role in access across suburban areas distant from central business districts; indeed, regional employment centers are understood as crucial features of the polycentric urban forms increasingly common.[13]

[8] (Ermagun 2021, Gobillon et al. 2007, Kain 1968)

[9] (Fan et al. 2012).

[10] (Chapple 2006, Immergluck 1998).

[11] (Fan et al. 2016).

[12] (Horner 2004, Joassart-Marcelli and Giordano 2006).

[13] (Bole 2011, Hartshorn and Muller 1989, Muller 2004).

Questions

This chapter develops and tests an approach for measuring access to multiple, inter-related destination types, and addresses the following questions:

- Is rail transit's presence and extent in a region related to increased multi-destination access?
- How does that relationship differ under varying regional economic conditions?

Specifically, we explore whether each census block group in six US regions has access by transit in 45 minutes or less to at least one major regional employment center and at least one public institution of higher education and at least one workforce development service provider based on the hypothesis that their combined benefits are contingent upon simultaneous access to all types of destinations.

Methods

This chapter examines rail access to social mobility-related destinations through a cross-sectional comparison of six US regions with each other. Such a comparison across regions allows us to test the access outcomes of different transit system designs and modal mixes under the same national, macroeconomic conditions. By selecting regions with significant variation in levels of rail investment and deployment yet broadly similar regional economic strength at the time of data collection, we can partially isolate the relationship between a transit system's modal mix and the access to opportunity it provides. We begin by selecting three fast-growth regions, one with a relatively extensive rail system, one with mainly bus service but a more modest amount of rail and one with a conventional bus-only transit system. Specifically, we selected Denver (large rail) the Twin Cities of Minneapolis and St. Paul, Minnesota (small rail) and Indianapolis (bus only).

Table 11.1 shows the regions selected for the analysis along with basic regional economic characteristics. Denver and Indianapolis both have generally similar populations and GDPs – as well as more similar GDPs per capita – and have experienced robust GDP growth in recent years. Denver has a well-developed regional rail system, currently of significantly greater extent than that of the Twin Cities, while Indianapolis had yet to implement any fixed-guideway transit at all at the time of data collection. Population density and transit ridership show a less-clear divide between the two groups of regions, with New Orleans, having a higher density than Denver, and nearly double the annual transit ridership of Indianapolis despite having a significantly smaller population. The inter-regional variation in transit ridership overall is significant, with Birmingham (slow growth, bus-only) having 2.73 annual rides per capita and Denver (fast growth, large rail system) having 37.12. Note also the weakness of the traditional relationship between metropolitan population density and ridership among the fast-growth regions, with Denver having the lowest density and highest ridership, and the Twin Cities having nearly 10 times the ridership of Indianapolis, despite only marginally higher density.

In addition to the three regions mentioned above, we include a parallel group of three slow-growing regions to examine the access implications of rail transit in differing regional economic circumstances. Memphis, New Orleans and Birmingham are all

Region		GDP 2017	GDP 2012-17	Population	Density (people /km²)	Annual Transit Ridership	GDP per capita	Rail (km)	Rail (stations)
Fast Growth	Twin Cities	$226,152M	11%	3,397,781	199	84,553,891	$66,559	100	37
	Denver	$185,942M	18%	2,798,684	137	104,032,685	$66,439	195	79
	Indianapolis	$122,608M	12%	1,989,032	186	8,571,322	$61,642	0	0
Slow Growth	Memphis	$62,059M	1%	1,038,617	113	6,217,400	$59,752	10	25
	Birmingham	$55,927M	3%	1,144,097	94	3,124,125	$48,883	0	
	New Orleans	$67,023M	2%	1,260,660	153	15,242,465	$53,165	35	109

Table 11.1: Comparison of study regions

similar in terms of the same regional economic comparisons as the fast-growth regions. In addition, though none of these three has a light rail/commuter rail transitway system, two – New Orleans and Memphis – have heritage streetcar systems, which are more common in smaller, slower growing regions. Paralleling the relationships of the fast-growth regions' transit systems, the New Orleans streetcar system is quite extensive, the Memphis system much less so; like Indianapolis, Birmingham has a bus-only system. Figure 11.1 shows the studied metropolitan regions[14] and the broader US regions in which they are located.

[14] Specifically Metropolitan Statistical Areas defined by the Census Bureau based on commute flows.

Figure 11.2 shows fluctuations in transit service throughout the day in our study regions as a percentage of peak-level trip originations by hour. Though early morning and late-night service levels are low to match demand, four of the six regions operate at least 70% of peak service throughout the midday period between morning and evening peaks. The two larger systems which do not, Denver and the Twin Cities, operate large amounts of peak-only express bus service, and at many locations still offer similar or better service than smaller systems with less of a valley between peaks. With the exception of one line in the Twin Cities, all rail lines studied provide all-day, bidirectional service. (All systems also have integrated bus-rail fares, with rail users paying the regular local or express/regional fare as appropriate, with the exception of higher rail fares to reach the Denver airport and the outermost three stations on the Twin Cities lone commuter rail line.) As such, though our analysis most directly measures transit system performance at peak service, it still provides a reasonable overall performance measure which is simple to both calculate and interpret.

Figure 11.1: Regions Studied

Data source

The access analysis centers on several basic types of data: transit route and schedule data produced by transit authorities, geographic, employment and demographic data provided by the Census Bureau and addresses of educational institutions and workforce development service providers collected by the researchers from individual institutions, university systems and state/county agencies.[15] Table 11.2 shows specific data types and sources.

[15] Researchers addressed a lack of systematic geospatial data by constraining the scope of the data to public colleges, universities and community colleges as well as publicly sanctioned workforce development service provider, allowing listings to be obtained through state and county agencies. Addresses from this process were then geocoded for use alongside existing geospatial data sets.

Data preparation

The GTFS feeds along with street data from the Census Bureau form the basis of a machine-readable network data set, which describes the locations of transport links, how they connect with one another and what they cost in time to traverse. This network

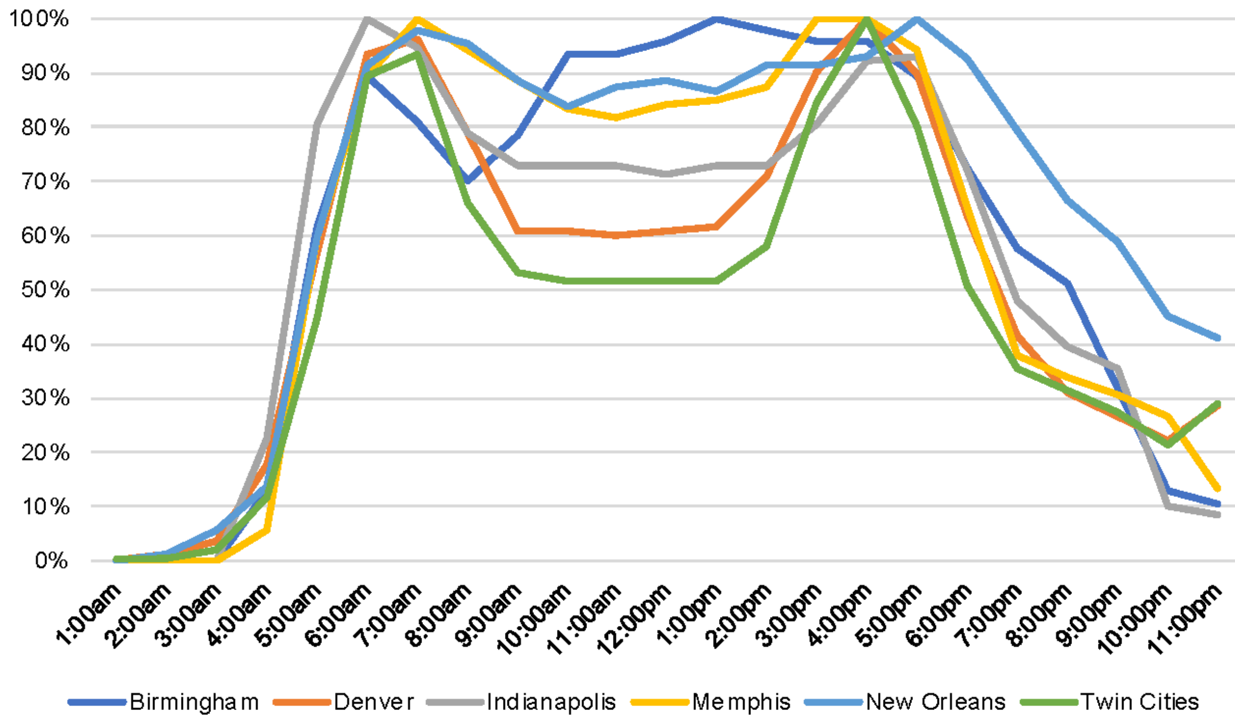


Figure 11.2: Temporal variation in transit service

data set is then used to compute polygons describing the geographic area reachable in 45 minutes or less of walk-ride-walk transit travel from every census block group within five kilometers (three miles) airline distance of a transit stop in one of the studied regions under current conditions. This inclusion standard ties the overall area of analysis organically to the general proportions of each metropolitan area's transit system without skewing the results by only considering units of analysis (block groups) within prime walking distance of transit. In other words, though we consider block groups with both high and low access to transit, we exclude block groups where non-park-and-ride access to transit is functionally absent. This exclusion is important because the political jurisdictions which fund and operate public transit in the United States do not necessarily align with the Census Bureau's statistical definition of a metropolitan area, and larger regions in particular may contain suburban cities or counties which do not participate in the fixed-route transit system.

Purpose	Data set	Provider
Transit routes and schedules	GTFS	Transit authorities
Census geographies and streets	TIGER/Line	Census Bureau
Employment	LEHD	Census Bureau
Demographics and travel behavior	ACS	Census Bureau
Colleges and workforce centers	-	Original data collection

Table 11.2: Data source

Access calculations use a uniform starting time of 8:00am on a weekday. Though transit service levels vary throughout the day, 8:00 AM shows the transit system at our near peak utilization; service levels at weekday peak affect a disproportionate number of travelers. In addition, a constant 8:00 AM access measure has been shown to perform similarly to dynamic measures which average access throughout the day in predicting transit mode share, suggesting 8:00 AM access offers a reasonable measure of transit system performance.[16]

[16] (Boisjoly and El-Geneidy 2016).

For the sake of consistency between measures of access to educational institutions and workforce development service centers versus access to employment, we compute access to all three destination types in terms of individual regional destinations, considering employment access in terms of binary access to at least one regional employment center as opposed to cumulative access to individual jobs.

Every block group, educational institution and workforce development service center which intersects one of these polygons is considered a potential destination for the origin block group. Destination block groups with a job density more than one standard deviation greater than the regional mean are identified as regionally significant employment centers which offer job seekers a wide range of options. This employment standard for regional significance is intended to allow for direct comparisons of employment access between regions with widely differing sizes, densities and economic circumstances by measuring how much the job density of a given area stands out from its surroundings as opposed to how dense it is in the absolute. Block groups with 45-minute transit access to at least one employment center and at least one public university or community college and at least one workforce center are identified by the binary variable All 3 Access, which is the response variable for the analysis.

Analysis approach

We begin by mapping locations of block groups with access to all three destination types in relation to majority-minority Areas of Concentrated Poverty (ACP50s): block groups in which over 40% of residents live on less than 185% of poverty and in which over 50% are people of color.[17] We also cross-tabulate population, race, and poverty by residence in a block group with access to all three destination types and graph the results. Finally, to more systematically examine determinants of access to opportunity, we estimate a binary logistic regression model to explain the probability of a block group having access to all three destination types as a function of transit system characteristics, location in the city and demographic characteristics. Our model includes the following variables:

[17] In the United States, the official poverty standard of $24,600 for a family of four as of 2019 is an inadequate measure of a livable income. The Census provides aggregate data on counts of families by categories of the ratio of their income to the poverty line. At $45,510, the income cutoff for 185% or less of poverty falls roughly halfway between the poverty line and national median household income of $68,703, offering a compromise between numbers of disadvantaged individuals considered and the depth of their disadvantage.

- ALL 3 ACCESS: Binary response variable identifying block groups with access to at least one employment center and at least one public university or community college and at least once workforce center.

- RAIL: Ordinal explanatory variable describing proximity to the nearest rail transit station

  We use a categorical variable (see Table 11.3) measuring proximity instead of a continuous variable measuring distance to allow the same variable for all regions, including those without rail, as a conventional distance-to-rail variable would be meaningless in Indianapolis and Birmingham. These distance ranges account for the spacing of parallel transit routes in higher-access areas; i.e. a rail station is likely the closest transit in a given direction for block groups within 400 m (0.25 mi), but much less likely so for block groups over 800 m (0.5 mi). In other words, more of any access differences found at longer distances is likely due to variations in bus service as opposed to rail. We hypothesize block groups more proximate to rail transit will have a higher probability of having access to all three destination types due to relatively high transit mobility.

Indicator	Network Distance
0	> 1.6 km (1 mi.)
1	800 m – 1.6 km (0.5-1 mi.)
2	400-800 m (0.25-0.5 mi.)
3	< 400 m (0.25 mi.)

Table 11.3: Definitions of ordinal explanatory variable describing proximity to the nearest rail station

- DISTANCE FROM DOWNTOWN: Continuous explanatory variable measuring airline distance to the central business district of the

region, with a unit of 1.6 km (1 mi.). We hypothesize block groups closer to their region's downtown will have a higher probability of having access to all three destination types due to relatively high transit mobility and geographic concentration of destinations in dense areas.

- Residents Below 185% Poverty: Continuous explanatory variable measuring residents whose households fall below the threshold used for determining ACP status, measured in percent. We hypothesize block groups with more low-income residents will have a higher probability of having access to all three destination types due to concentrations of poverty, traditional transit service and potential destinations in inner cities.

- People of Color: Continuous explanatory variable measuring residents who self-identify as non-white and/or Hispanic, measured in percent. In other words, 100% minus the percentage of white, non-Hispanic residents in the block group. We hypothesize block groups with more POC residents will have a higher probability of having access to all three destination types due to concentrations of POC residents, traditional transit service and potential destinations in inner cities.

- Transit Commuters: Continuous explanatory variable measuring workers who primarily commute using public transit, measured in percent. We hypothesize block groups with more transit commuters will have a higher probability of having access to all three destination types due to transit systems planning around demand and concentrations of traditional transit service and potential destinations in inner cities.

- Workers in Carless Households: Continuous explanatory variable measuring workers who live in households without a motor vehicle, measured in percent. We hypothesize block groups with more workers in carless households will have a higher probability of having access to all three destination types due to strong incentives to purchase a car in areas with low transit access.

- FAST-GROWTH REGION: Binary explanatory variable identifying block groups in the Twin Cities, Denver or Indianapolis regions. Individual regional variables cannot be included due to collinearity caused by Indianapolis and Birmingham both having all 0-values for Rail. We hypothesize block groups in fast-growth regions will have a higher probability of having access to all three destination types due to proliferation of employment centers in strong regional economies and greater resources for transit.

The expected relationships between the four demographic variables and the probability of having access to all three destination types may appear straightforward, but these variables provide an opportunity to evaluate whether any increased multi-destination access provided by rail transit is shared equitably. Though we considered estimating separate models for each region, we ultimately rejected this modeling approach as it would have precluded using the same variables in each case for comparability as all values of any measure of rail proximity would be zero for Indianapolis and Birmingham.

Findings

Figure 11.3 through Figure 11.8 show locations of ACPs and ACP50s (shown by hatch pattern) by access to one or more destination types (shown by color). For example, a red-shaded area with no hatching has access to an employment center and is not an ACP or ACP50; a blue-shaded area with a simple hatch pattern has access to a public higher-education institution and is a (majority-white) ACP; a purple-shaded area with a cross hatch pattern has access to both an employment center and public higher-education institution and is an ACP50.

Notably, the bus-only regions perform worst for access to all three destination types (shown in brown), with only a small area with access to all three destination types in Birmingham (accounting for 4% of total population in ACP50s), and no such areas at all in Indianapolis. Upon inspection of educational institution and workforce center address lists, Indianapolis has few of either, all of which are distant from each other. Both Birmingham and Indianapolis have large areas with access to an employment center, potentially indicating a heavy downtown focus in their transit systems. In both cases, this is combined with access to one

other destination type (workforce development services in Birmingham and public higher education in Indianapolis) in central areas, but with little or no access to either additional destination type independent of access to an employment center. Indianapolis manages to provide access to one or two destination types for most of its ACPs and ACP50s; Birmingham, however, shows large areas of both having no access.

Memphis and New Orleans have significant areas with access to all three destination types in their urban cores, with 18% of Memphis ACP50 residents having access to all three destination types and 31% in New Orleans. These central areas of high multi-destination access are roughly surrounded by block groups with access to two destination types, but not all three, giving way to a patchwork of block groups with access to one or two destination types – or none at all – further out. Memphis and New Orleans also both have large areas of ACP50s with no access, though in both cases most of the area with access to all three destination types lies within an ACP50.[18]

[18] Note that the outer areas of both regions include a number of very large block groups with very little population due to development restrictions along the Mississippi River and/or the shores of Lake Pontchartrain.

Denver and the Twin Cities both show much larger accessible areas under current conditions, with access to all three destination types currently somewhat more prevalent in Denver (with 50% of ACP50 residents having all 3 access destination types, compared with 48% in the Twin Cities), potentially reflecting the more advanced state of Denver's regional transitway system. The two regions differ, however, in their spatial distributions of access: Access to all three destination types in the Twin Cities is heavily concentrated in the central cities of Minneapolis and Saint Paul, but is spread more widely across the region in Denver, with pockets of access well out into the suburbs and a significant sub-center of access to all three destination types to the east of downtown roughly surrounding the junction of two rail lines. Both regions provide most of their ACP50s with access to at least one destination type, though both show large ACP50 areas with access to only one or two destination types as well as large areas which are neither ACPs nor APC50s and have access to all three.

Descriptive analysis

Figure 11.9 shows a region/scenario breakdown of percentages of Metropolitan Statistical Area (MSA) populations with access to all three destination types by race. Denver and the Twin Cities once

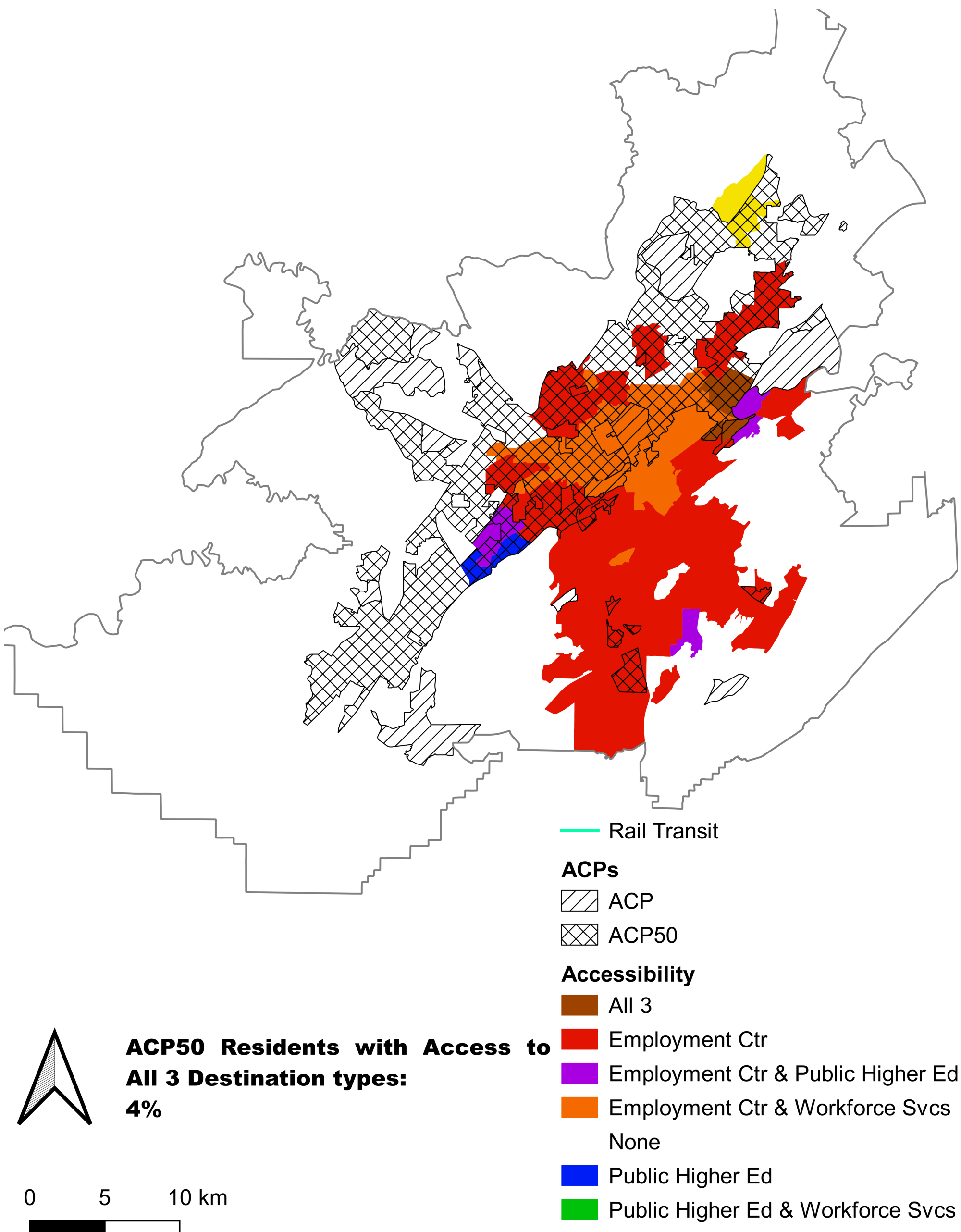


Figure 11.3: Access and ACPs Birmingham

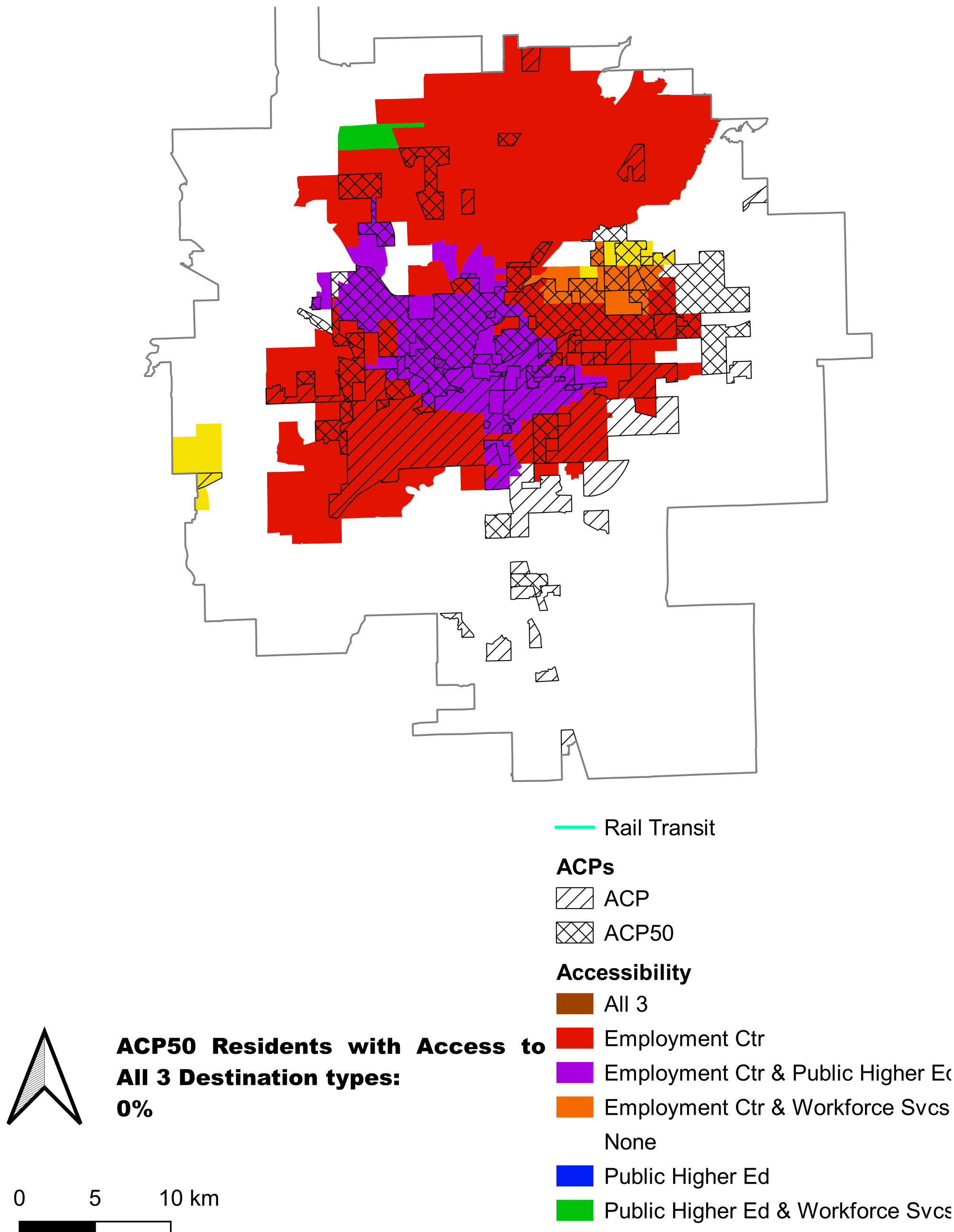


Figure 11.4: Access and ACPs in Indianapolis

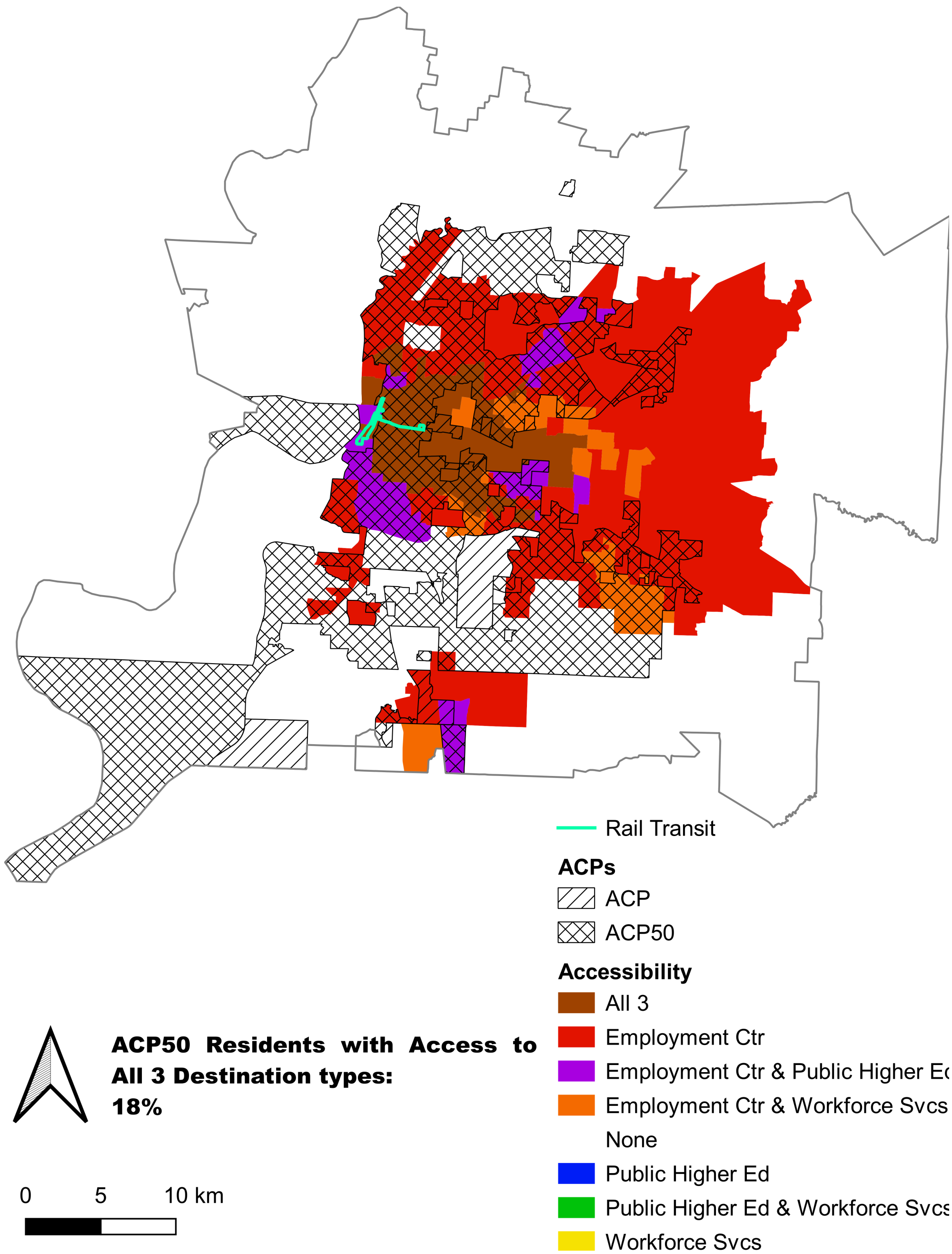


Figure 11.5: Access and ACPs in Memphis

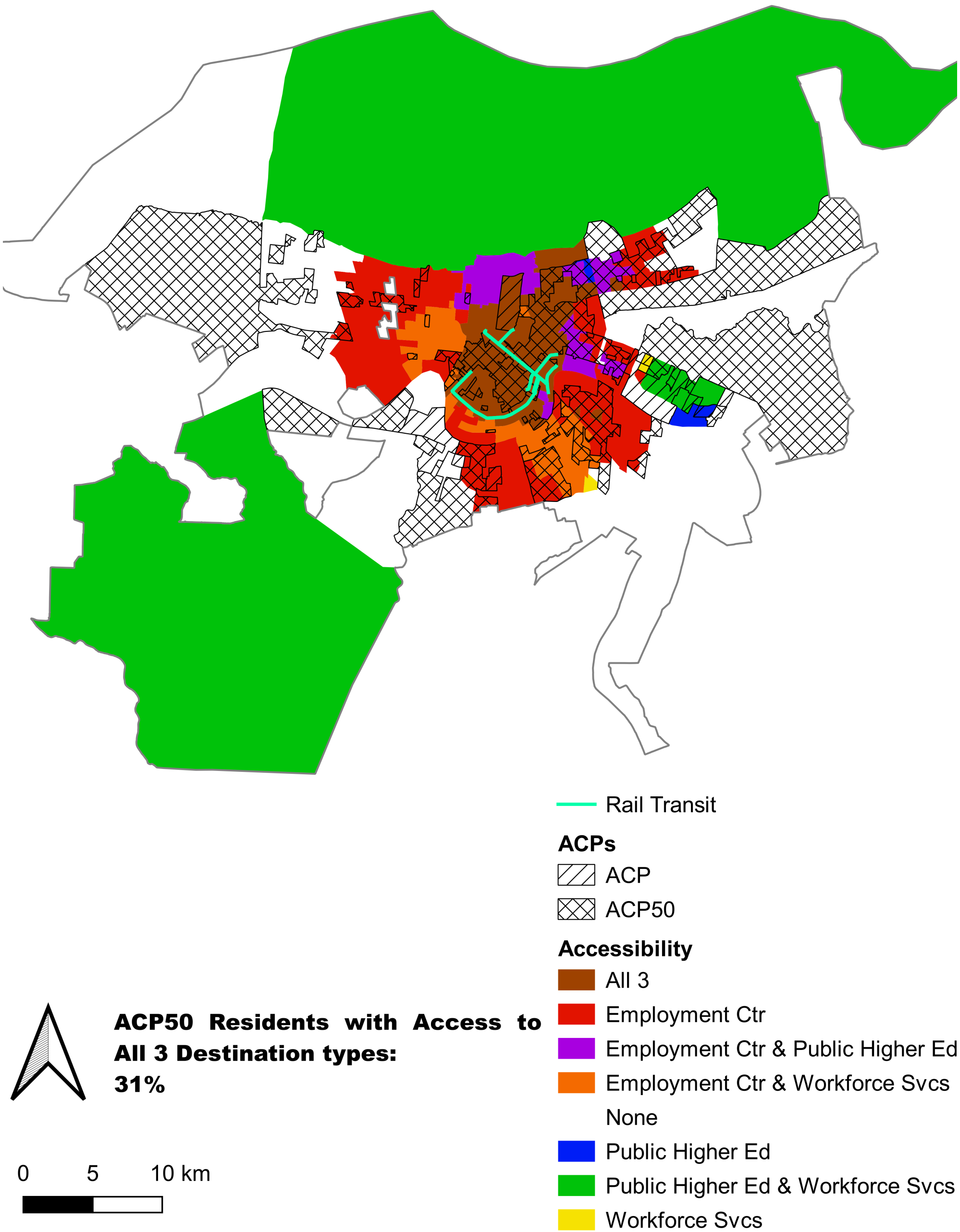


Figure 11.6: Access and ACPs in New Orleans

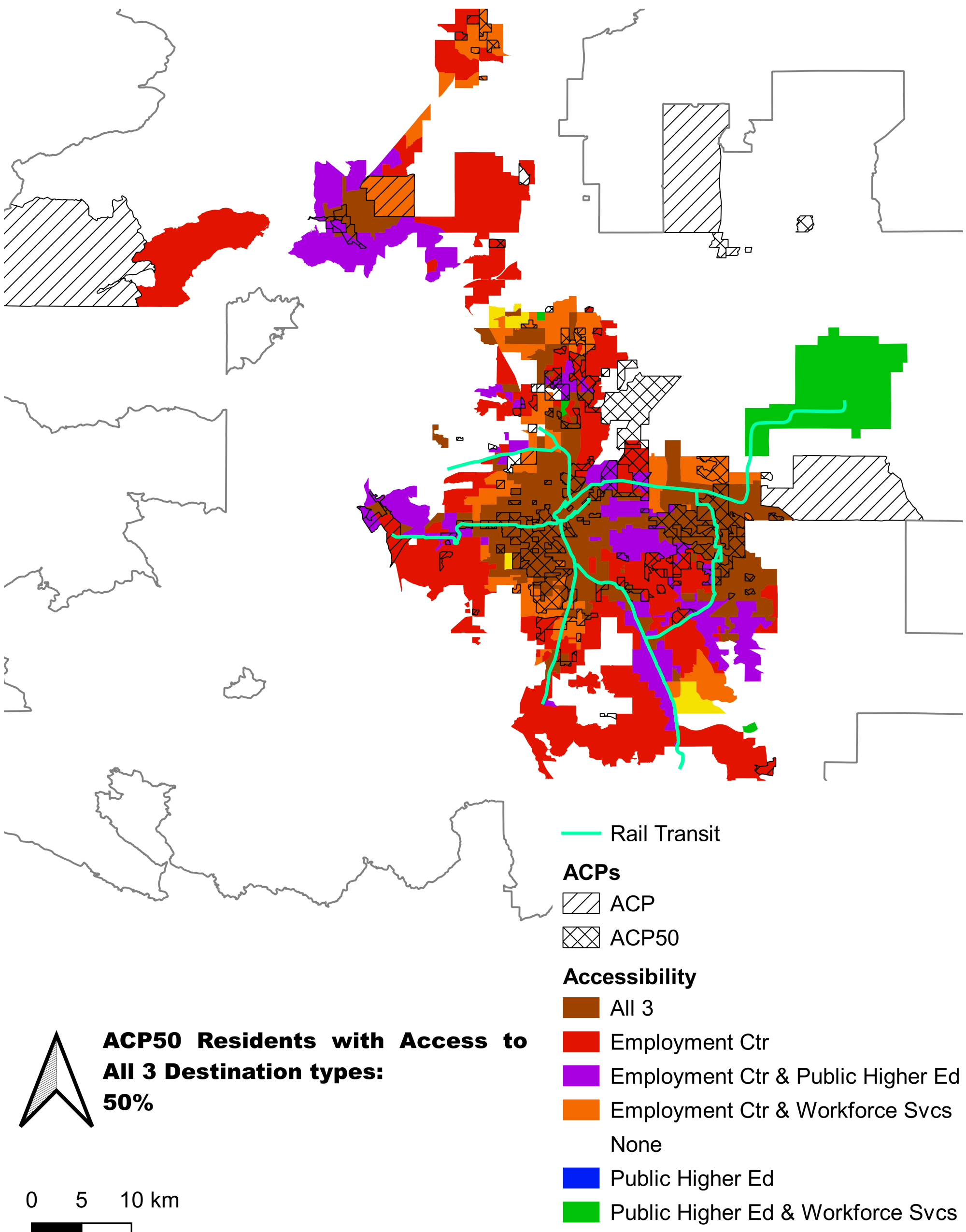


Figure 11.7: Access and ACPs in Denver

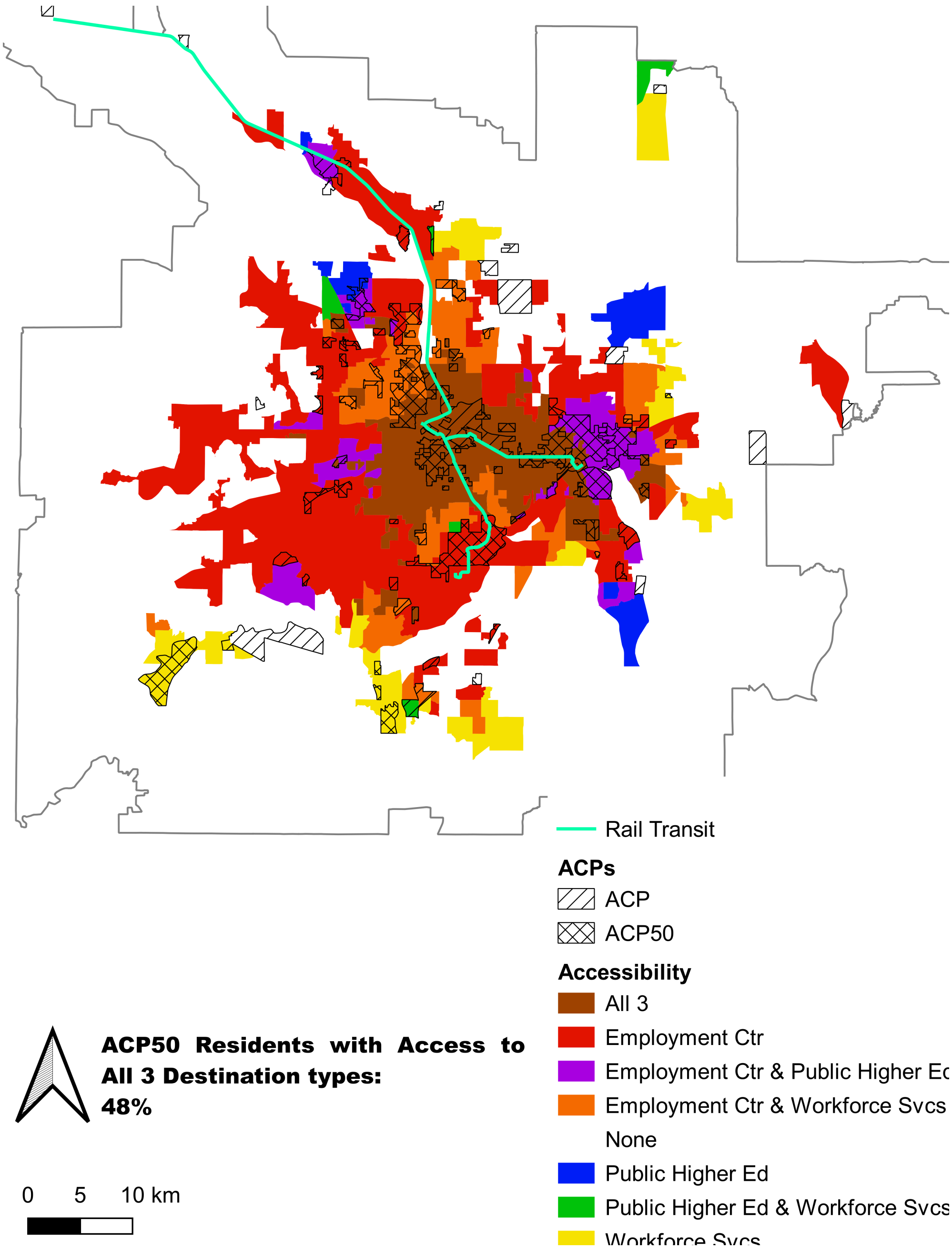


Figure 11.8: Access and ACPs in the Twin Cities

again outperform the other regions, with New Orleans showing the best access of the slow-growth regions.

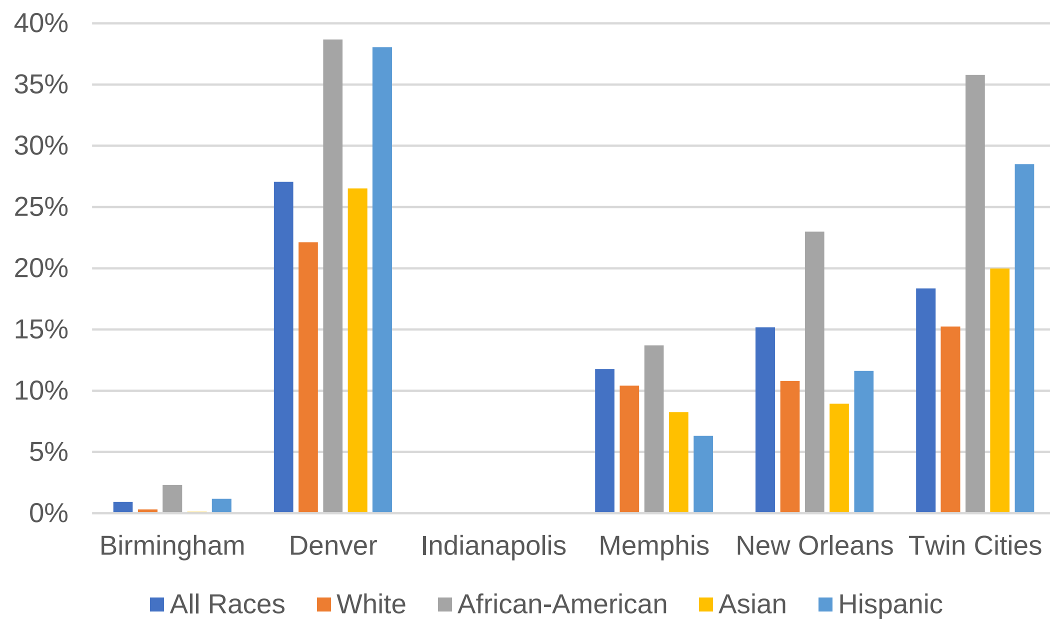


Figure 11.9: Access by race

Notably, people of color are more likely than whites to live in block groups with access to all three destination types than whites, with African Americans having the highest levels of access in all regions and scenarios. This difference in access levels is smallest in Memphis, with African Americans only four percentage points more likely than whites to have access to all three destination types.

Figure 11.10 breaks down access by household income relative to the Federal poverty standard. Much the same inter-regional pattern appears as in Figure 11.8, with Denver and the Twin Cities performing best across income levels. In all cases, poorer residents have higher access levels than wealthier residents, though these differences are less in the three slow-growth regions.

The left side of Table 11.4 presents descriptive statistics of the variables included in regression analysis. Notably, most block groups studied do not have access to all three destination types and more than twice as many workers live in households without a motor vehicle than regularly commute by transit, indicating a potential unserved need for transit access.

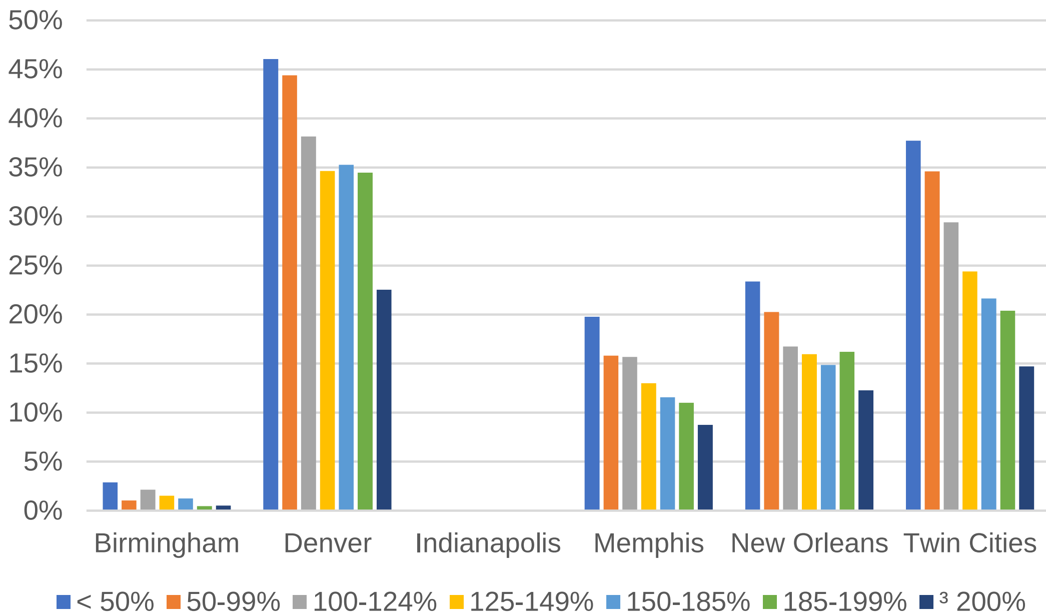


Figure 11.10: Access by income relative to poverty

Regression analysis

The right side of Table 11.4 presents the results of the multi-region, cross-sectional logistic regression model. Proximity to rail transit stations is associated with a large increase in a block group's odds of having transit access to all three destination types; specifically, each unit of increase in the ordinal variable Rail corresponds to roughly a seven-fold increase in those odds. Not surprisingly given the downtown focus of most US transit systems, each additional 1.6 km (1 mi.) of airline distance from the central business district corresponds to a 12% decrease in the probability of a block group having access to all three destination types.

A block group is slightly less likely to have access to all three destination types the more low-income residents it has, but slightly more likely the more people of color. Though these variables are correlated, their bivariate correlation of < 0.8 does not raise undue concerns of collinearity. This pattern could indicate spatial differences in concentrations of poverty by race, i.e. poor people of color concentrated in the inner city (with higher transit service levels) and poor whites in the suburbs (with lower service levels). Block groups with higher percentages of regular transit commuters

Variable	Mean	Std. Dev.	Coefficient		Odds Ratio
All 3 Access (binary)	0.22	0.41			
Rail (ordinal)	0.12	0.46	1.932	***	6.903
Distance from Downtown (km)	15.51	12.23	-0.126	***	0.881
Residents Below 185% Poverty (%)	30.00	22.40	-0.004	*	0.996
People of Color Residents (%)	40.20	30.81	0.032	*	1.033
Transit Commuters (%)	4.60	4.94	0.173	***	1.189
Workers in Carless Households (%)	11.71	29.46	-0.008	**	0.992
Fast-Growth Region (binary)	0.70	0.45	0.765	***	2.150
Constant			-1.917	***	0.147
No. of Observations					6,679
LR $\chi^2(7)$					2,275.87
Prob $>\chi^2$					0
Pseudo R^2					0.320

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 11.4: Descriptive statistics (left) and Binary logistic regression (right). Dependent variable: All 3 Access

are more likely to have access to all three destination types, though it is unclear from the model what direction any causal relationship involved operates. Transit systems are planned to serve areas with high demand, but high levels of access also tend to encourage ridership. Each percentage point increase in Workers in Carless Households, however, corresponds to roughly a 1% decrease in the probability of a block group having access – in other words, the two are inversely proportional. This pattern indicates some degree of mismatch between levels of transit service provided and levels of transport disadvantage among residents. Finally, location in one of the three fast-growth regions (Denver, Indianapolis, and the Twin Cities) is associated with just over a twofold increase in the probability of a block group having access to all three destination types. This last finding is particularly notable with regard to Denver and the Twin Cities, as they account for all block groups in the fast-growth regions with access to all three destination types.

Conclusions

The results provide compelling evidence for a strong relationship between fixed-guideway transit investments and equitable access to opportunity. The difference in access between the two fast growth

regions with regional transitway systems and Indianapolis is particularly stark. The effect size found for proximity to rail transit also demonstrates the value of transitways in providing access to the destinations needed to prepare for, get and keep a good job.

It should be noted that a similar effect may exist for Bus Rapid Transit (BRT) as well. None of the regions studied had true, dedicated guideway BRT in operation at the time of data collection. As a result, our rail variable effectively measures both mode and fixed-guideway status, and with no fixed guideway bus services to compare, it is impossible to determine how much of the effect is due to which. However, rail-served areas in the slow-growth regions are served by heritage streetcar stops, which do not generally offer more rapid regional mobility than conventional buses. In these instances, however, rail may support the development of a dense, destination-rich environment, in which access is high despite mobility being low.[19]

[19] (Levine et al. 2012).

In addition to underscoring the importance of fixed-guideway transit, the results also indicate the importance of planning transit systems for regional-scale transit access to a variety of destination types, regardless of transit mode employed. A high level of traditional bus service may allow some degree of similar multi-destination access. In addition, a multi-destination regional access planning perspective also heightens the importance of integrated transit, land use and regional public service planning. The social equity implications of rail are also impossible to ignore in these results. By every measure considered, more extensive fixed-guideway transit systems not only offer greater access overall, but greater racial and economic justice in terms of access as well.

Next

The results underscore the importance of considering access from a variety of perspectives in regional transit planning – including from the perspective of providing access to multiple, mutually critical destinations. Our approach can be understood as measuring whether or not areas of a city have at least some transit access to all of the destinations a resident would need to accomplish a specific purpose. In this case, the purpose was obtaining the training and job search skills one needs to be hired for a job and actually commuting to that job, but the method is applicable for other

complementary destination types as well – even many not directly related to employment.

Future research based on the work described here could explore specifically how land use and mobility combine to produce differing levels of multi-destination access in different cases, or could also add other non-job search-related destinations important to working people's daily living, such as childcare centers and full-service grocery stores. Finally, since the time of data collection, rapid bus services and broader system restructurings have been completed or begun in Indianapolis and Memphis, while other cases continue to improve their transit systems as well, offering strong potential for follow-up research. We believe the access analysis approach put forth in this chapter offers planners a simple tool for ensuring transit systems serve the destination types their users need to access.

12

Non-work Vehicle Trip Generation from Multi-week In-vehicle GPS Data

Arthur Huang and David Levinson

Abstract: This chapter examines the impact of land use round home on vehicle trip generation using in-vehicle GPS data from the Minneapolis - St. Paul Metropolitan Area in 2008. We identify correlation of trips made by the same individual in the trip generation models. To control for this effect, five mixed-effects models are systematically tested: mixed-effects linear model, mixed-effects log-linear model, mixed-effects negative binomial model, and mixed-effects ordered logistic model. The mixed-effects ordered logistic model produces the highest goodness of fit for our data and therefore is recommended. The empirical results indicate that although access around home is not found to have statistically significant effects on non-work vehicle trips, the diversity of services within 10 to 15 minutes and 15 and 20 minutes from home can help reduce the number of non-work vehicle trips.

Introduction

Keywords: GPS data; Land use; Trip generation; Access; Service diversity

Modeling the trip generation, the first step of the traditional four-step travel demand model, received a significant attention by transport researchers and practitioners. Much of the previous studies examine the influence of the built environment on vehicle trip generation. Most studies found that land use influences vehicle trip generation.[1] Explanatory variables have included: residential or

[1] (Handy 1996, Levinson and Krizek 2008, Schwanen et al. 2004, Scott and Horner 2008).

employment density, availability and quality of transit services, pedestrian access, distance to destinations, mixed land use, destination access, parking supply and cost, vehicle ownership, socio-demographics, attitudes toward mode choice, residential location choice, and street design. Examples of dependent variables include: trip frequency, Vehicle Miles Traveled (VMT), household trip generation rate, and the proportion of trips using a particular mode.

Models for trip generation include linear, log linear, Poisson or negative binomial, Tobit or Logit, and factor analysis. The research is mixed on which is best. Studies show that (1) the negative binomial (NB) model is a better fit than the Poisson model for shopping trip frequency[2], (2) Tobit models perform better than the linear models to predict person-level disaggregate trip generation,[3] (3) negative binomial model and the modified Poisson models improve reliability when there are over-dispersion and heterogeneity in the count data,[4] (4) ordered probit model performs better than the linear, log linear, Poisson, and NB, for trips with various purposes,[5] and (5) a zero-inflated negative binomial (ZINB) model to estimate the frequency of commuting trips by bicycle fit the data better than NB and logistic models.[6] Overall, findings suggest that count-data models work better than linear models in modeling trip generation.[7] Most models, however, are fixed-effects models based on travel survey data. It is still unclear whether they can be properly applied to GPS travel data.

[2] (Barmby and Doornik 1989).

[3] (Cotrus et al. 2005).

[4] (Jang 2005).

[5] (Lim and Srinivasan 2011).

[6] (Schoner and Cao 2013).

[7] (Ermagun et al. 2018).

The travel data used were mostly based on paper-and-pencil surveys where individuals were asked to reflect upon their past travel experience. Advances of GPS and GIS technologies provide new opportunities and challenges for investigating trip generation of non-work trips. According to Draijer et al.,[8] GPS devices have the following advantages over traditional paper-and-pencil diary methods:

[8] (Draijer et al. 2000).

1. Real-time spatial and temporal information of a trip is available, such as distance, travel times, travel speed, and route information.

2. Fewer misreporting or underreporting of trips.

3. Data are stored in digital formats.

4. The subjects' burden of reporting travel information is reduced.

Therefore, GPS data can better incorporate trip information for modeling trip generation than traditional data collection methods.

A challenge is that one person makes multiple trips or travel decisions over a certain period of time in the GPS data, which suggests that there may exist correlations among observations. How to appropriately select a model is a key issue.

Questions

This chapter aims to examine various model structures for modeling vehicle trip generation based on the in-vehicle GPS data in the Minneapolis-St. Paul Metropolitan Area. In particular, it addresses the following questions:

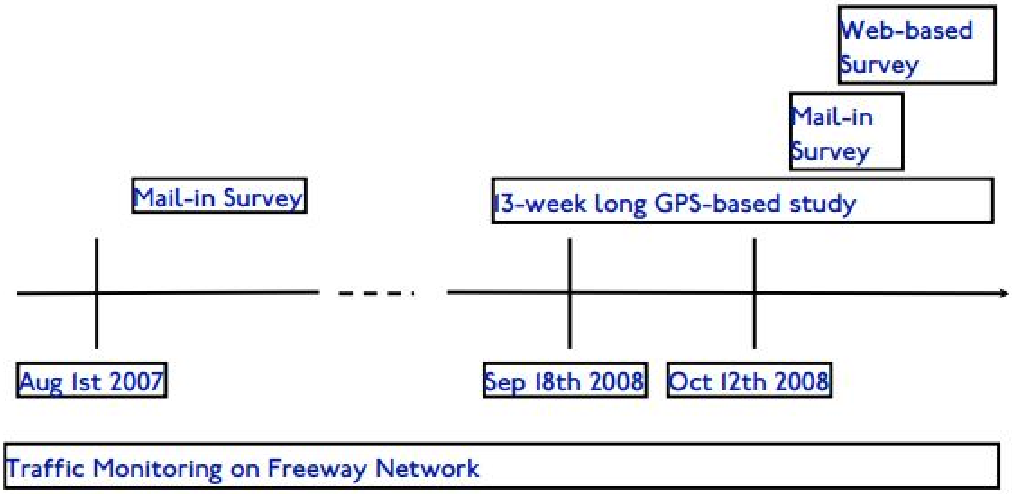
- How appropriate are the mixed-effects model structures for in-vehicle GPS data with repeated observations for individuals?
- Which five mixed-effects model structures in modeling non-work, non-home vehicle trip generation provides the greatest explanatory power?
- Which land use and access variables most impact non-work, non-home vehicle trip generation?

Methods

GPS Data

The GPS data collection process in the Minneapolis-St. Paul Metropolitan area lasted from September to December of 2008. The collection process includes three stages (Figure 12.1). The first stage is to recruit the subjects. The announcements on recruiting subjects were posted on various media such as Craiglist.com and Citypages.com and were sent out via other forms such as postcards handed out in downtown parking ramps and emails to 7000 University of Minnesota staff (excluding students and faculty). 141 subjects were selected for this chapter. After the subjects were selected, the second stage is to collect the data by installing GPS devices in selected subjects' vehicles. There were two types of GPS devices used. The first type was the real-time tracking GPS device provided by the subcontractor Vehicle Monitoring Technologies (VMTInc). A local subcontractors was hired to install the GPS devices.[9] The GPS devices recorded the coordinates of the vehicle every second while the vehicle is turned on. The second type of

[9] (Zhu 2010).



(Source: Zhu (2010))

Figure 12.1: The timeline of the GPS data collection process

devices was the logging GPS (QSTARZ BT-Q1000p GPS Travel Recorders). Different from the previous type, the data can only be exported manually at the end of the study. The GPS frequency was one point per 25 meters. Participants were asked to periodically fill surveys about their trips. The third stage is to process the GPS data points to create trip trajectories. Non-work, non-home trips are selected for this chapter.

Table 12.1 summarizes the subjects' socio-demographic information, which is compared with the overall socio-demographics of the Minneapolis-St. Paul Metropolitan Area. The percentage of women in our data is higher than the Twin Cities Metropolitan Area. In addition, more people in our data hold degrees above high school than the Twin Cities Metropolitan Area, which is probably influenced by some of the workers from the University of Minnesota. The overall income level in the GPS data is also higher than the Twin Cities Metropolitan Area, which is probably related with vehicle ownership (one needs to own a car to be qualified for this chapter) and higher educational level.

Descriptive statistics of non-work vehicle trips

Figure 12.2 shows the distribution of the number of daily non-work, non-home vehicle trips from all participants. The number of daily non-work, non-home trips ranges from 0 to 17 (16 is missing). In

Category	Variable	GPS data (%)	Twin Cities (%)
Gender	Male	41.25	49.40
	Female	58.75	50.60
Education	11th grade or less	0	9.40
	High School	13.09	49.60
	Associate	24.99	7.70
	Bachelor	45.22	23.20
	Graduate	16.69	10.10
Household Income	$< \$49,999$	20.20	45.20
	$\$50,000 - \$74,999$	30.73	23.30
	$\$75,000 - \$124,999$	29.44	14.60
	$> \$124,999$	20.16	16.90
Race	White	83.06	87.70
	Black	7.36	6.20
	Others	9.58	6.10

Table 12.1: Comparison of socio-demographics in the GPS data and the Twin Cities area

total, there are 1832 days with zero non-work, non-home vehicle trips, which is the highest frequency. The lowest frequency is the number of days with 17 trips with only two records. The average number of daily non-work, non-home vehicle trips equals 1.57 with standard deviation 1.86.

Figure 12.2: Histogram of daily non-work, non-home vehicle trips from the GPS data

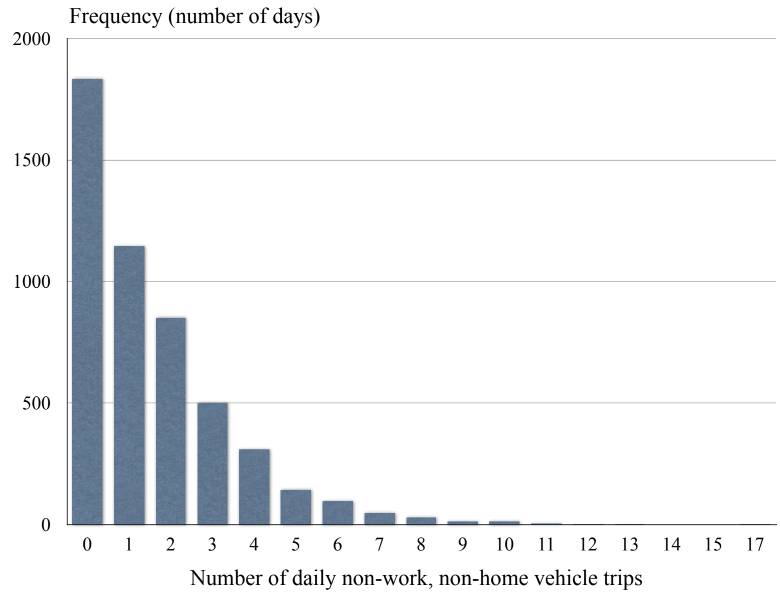


Table 12.2: Key percentiles of daily non-home, non-work vehicle trips

Percentile	Number
100th (max)	17
99th	8
75th	5
50th	1
25th	0
5th	0

Table 12.2 displays the distribution of the percentiles of the data. The 25th percentile is located at 0 trips and the median equals 1 trip. The 75th percentile of the data is located at 5 trips. For the rest of this chapter, unless otherwise specified, all trips refer to non-work, non-home vehicle trips. For the simplicity of presentation, the term"trips" will be used.

Independent variables

The independent variables used in this chapter include land use measures around home, day-of-week variables, and individuals' socio-demographics such as age, gender, and income.

To measure land use around home at the microscopic level, we create $[0, 5)$ min,[10] $[5, 10)$ min, $[10, 15)$ min, and $[15, 20)$ min driving zones around home using the road network with an estimated travel speed on each road. One example of the created driving zones is shown in Figure 12.3. The key land use measures include access and diversity of services (land use mix).

Access around home is measured with the cumulative opportunities measure,[11] which calculates the sum of the services within a zone. An assumption of this measure is that each service in

[10] The $[0, 5)$ min zone is the area between 0 minutes (inclusive) and 5 minutes (exclusive) driving from home.

[11] See chapter 1 in this volume.

a zone has an equal opportunity (likelihood) to be visited. We argue that it is approximately true as each zone is defined within a small time interval. The empirical tests reveal that the ln form of access produces greater goodness of fit for the models. Therefore, the ln form of the cumulative access measure in the four driving zones around home is employed. $A_{[0,5)}$, $A_{[5,10)}$, $A_{[10,15)}$, and $A_{[15,20)}$ respectively indicate the access measures in the $[0,5)$ min, $[5,10)$ min, $[10,15)$ min, and $[15,20)$ min driving zones from a subject's home.

The diversity of services or land use mix in a zone can be measured by the entropy index.[12] Using the $[0,5)$ min driving zone from home as an example, the diversity of services in this zone ($H_{[0,5)}$) equals:

[12] (Shannon 1948).

$$H_{[0,5)} = -\sum_{s=1}^{S} \rho_s ln(\rho_s) \tag{12.1}$$

Where ρ_s represents the proportion of service type s within the zone and S is the total number of available service types in this zone. The greater $H_{[0,5)}$ is, the more diverse services a destination has. Similarly we can measure the diversity of services in the $[5,10)$ min, $[10,15)$ min, and $[15,20)$ min driving zones from home, which are indicated by $H_{[5,10)}$, $H_{[10,15)}$, and $H_{[15,20)}$.

The hypotheses about the impacts of the independent variables on the number of daily trips are summarized in Table 12.3. There are two possible arguments about the relationship between access around home and the number of daily trips. The first argument is that all else equal, greater access around one's home can help reduce the number of daily trips because some of the short-distance trips may be replaced by non-vehicle travel modes. The second argument is that all else equal, greater access around home can increase the number of daily trips because it induces greater travel demand. For example, if there is a big shopping mall only 5 minutes' drive from home, all else equal, one may visit this mall more often (even just for window shopping or enjoying the facilities there) than the scenario where the mall is farther away.

It is hypothesized that diversity of services around home can reduce the number of trips because more types of services support multi-purpose shopping and comparison-shopping. By doing so, one may reduce the number of trips needed by visiting a location with multiple types of services. In addition, higher income may have a positive or negative effect on the number of trips. On the one

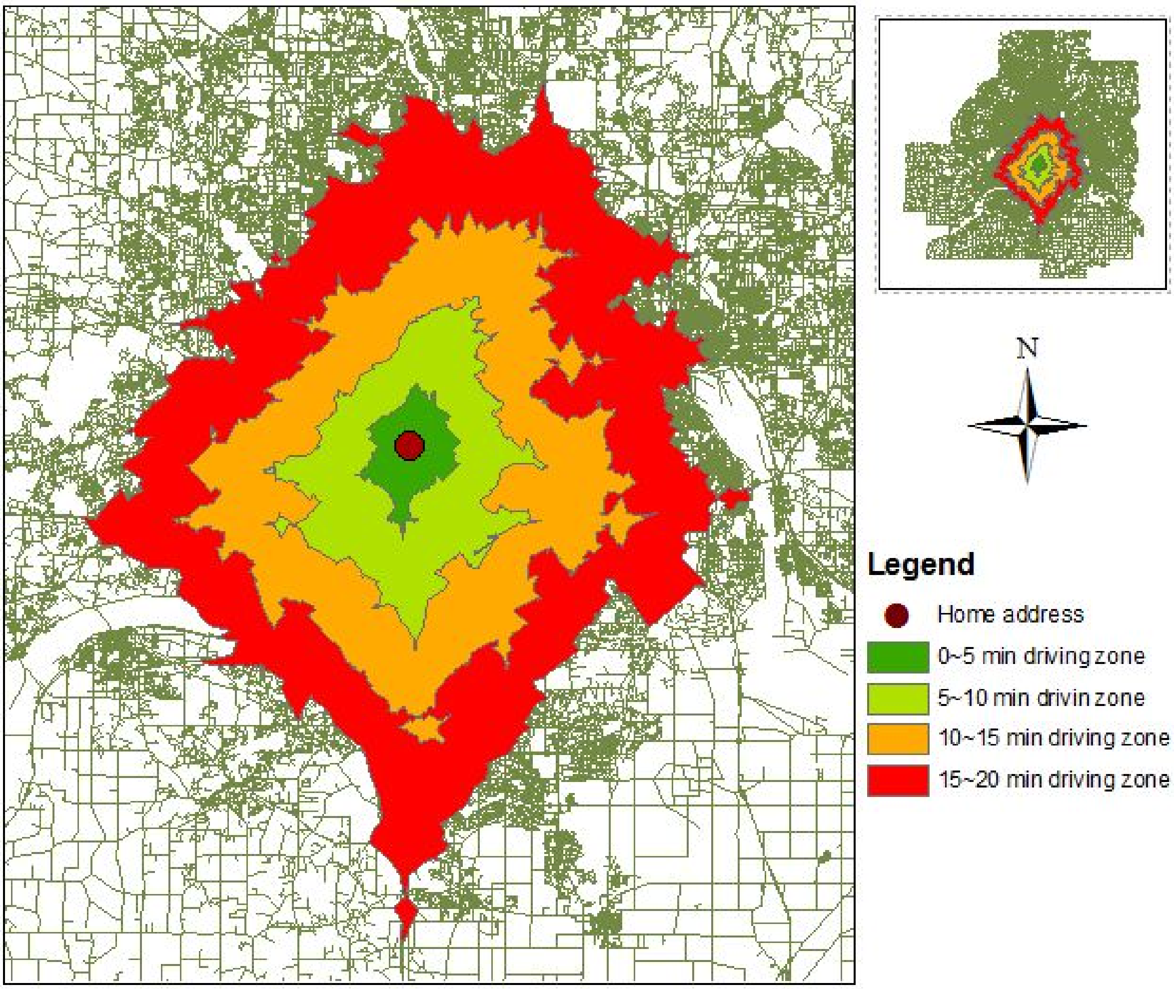


Figure 12.3: The $[0, 5)$ min, $[5, 10)$ min, $[10, 15)$ min and $[15, 20)$ min driving zones around home of an individual with GPSID 1036

hand, higher-income families have a greater financial capacity of making more trips. On the other hand, they may have a tighter work schedule and thus have less time for making those trips. In terms of day of week, trips are presumably more likely to happen at weekends than on weekdays.

In literature, five model structures have been employed to model trip generation: linear, log linear, Poisson/negative binomial, ordered logit, and zero-inflated Poisson/negative binomial models. Yet there is a lack of systematic comparison of the goodness of fit of various model structures in modeling vehicle trip generation with repeated observations for each subject. Traditional fixed-effects

models do not consider the correlations of dependent variables for the same subject. Therefore given repeated observations for each subject, random-effects models may be a better choice as such models incorporate an extra random-effect component for each subject to control for the heterogeneity. The mixed-effects linear, log linear, Poisson/negative binomial, ordered logit, and zero-inflated Poisson/negative binomial models are described as follows.

Table 12.3: Hypotheses on the impact of key independent variables and vehicle trip generation

Variable	Impacts
Access	$+/-$
Diversity of services	$-$
Income	$+/-$
Weekend	$+$

Model structures

For one individual, the mixed-effects linear model can be written as:

$$Y_t = f(b, \Lambda, S, W_t) \tag{12.2}$$

Where Y_t represents the number of trips by an individual on day t. b is the added random effect term for the individual generated from a standard normal distribution with mean zero. Λ indicates a vector of land use measurements around home. W_t is a vector of day-of-week dummy variables and monthly dummy variables.

Similarly, the mixed-effects log linear model for one individual can be expressed as:

$$ln(Y_t) = f(b, \Lambda, S, W_t) \tag{12.3}$$

In cases where Y_t equals 0, we use a small value 0.01 to replace 0 so that $ln(Y_t)$ is meaningful.

The mixed-effects Poisson model assumes that the conditional mean of the dependent variable is an exponential function of the explanatory variables (including the added random effect) and their coefficients. The probability of making Y_t trips can be written as:[13]

[13] Following the nomenclature in Jang (2005).

$$Pr(Y_t) = \frac{e^{-\lambda_t} \lambda_t^{Y_t}}{Y_t!} \tag{12.4}$$

Where Y_t is the number of trips (0, 1, 2...) and λ_t is the mean parameter of the model which is estimated as:

$$ln(\lambda_t) = f(b, \Lambda, S, W_t) \tag{12.5}$$

If the conditional variance exceeds the conditional mean, negative binomial model serves as a better fit than the Poisson model. Compared with the Poisson model, $ln(\lambda_t)$ in the negative binomial model has an extra unobserved heterogeneity term ϵ_t which follows Gamma distribution:

$$ln(\lambda_t) = f(b, \Lambda, S, W_t, \epsilon_t) \tag{12.6}$$

For the mixed-effects ordered logit model, if the number of daily trips are categorized into Z groups, the utility of making Y_t trips for one individual can be written as:

$$U_t = f(b, \Lambda, S, W_t, \epsilon_t) \tag{12.7}$$

Where ϵ_t is an error term that assumes to follow the logistic distribution.[14] While we cannot observe U_t, we can observe the categories of daily trips, which can be represented as:

[14] See (Becker and Kennedy 1992) for details.

$$Y_t = \begin{cases} 0 & \text{if } U_t \leq \delta_0 \\ 1 & \text{if } \delta_0 \leq U_t \leq \delta_1 \\ .... & \\ z & \text{if } \delta_{z-1} \leq U_t \leq \delta_z \\ .... & \\ Z & \text{if } \delta_{Z-1} \leq U_t \end{cases} \tag{12.8}$$

The probability that one individual makes z trips on day t can be written as:

$$P(Y_t = z) = \Phi(\delta_z - U_t) - \Phi(\delta_{z-1} - U_t) \tag{12.9}$$

Where $\Phi(\cdot)$ represents the standard normal cumulative distribution function. The next step is to select an appropriate number of Z by systematically comparing the mixed-effects logit models with different numbers of categories of trips.

The zero-inflated Poisson/negative binomial model structure aims to model count data with an excess number of zeros.[15] The model takes two steps. The first step adopts a binary logit function to predict the probability of producing 0 vehicle trips. The second step incorporates the probability of producing more than 0 vehicle trips (which is the complement of the previous result) for the non-zero data using the Poisson/negative binomial structure. In our data, the utility function for estimating 0 trips for one individual can be written as:

[15] (Lambert 1992).

$$U(Y_t = 0) = f(a, W_t, \epsilon_t) \tag{12.10}$$

Where ϵ_t is a random-effect term that follows the logistic distribution and W_t is a vector of day-of-week variables. It hypothesized that a subject is more likely to make 0 trips on weekdays than on weekends. a is an extra random effect term for a subject and it follows a normal distribution with mean zero. This

term is used to control for the heterogeneity of decisions made by the same subjects.

After predicting the probability of having 0 trips, the remaining trip counts occur with a probability calculated by 1 minus the probability of making 0 trips. And the remaining trip counts presumably follow the Poisson/negative binomial distribution as described before. The utility for a non-zero vehicle trip count ($y_t > 0$) equals:

$$U(Y_t = y_t) = f(b, \Lambda, S) \tag{12.11}$$

Where Λ indicates a vector of land use measurements around home. S is a vector of personal socio-demographic variables. We add another random-effect term b for each subject to control for heterogeneity among observations. Like a, b also presumably follows a normal distribution with mean zero. But the distributions of a and b are set to have different standard deviations in the estimation process.

Findings

Identifying random effects

To examine whether there exist extra random effects, we plot the residuals versus fitted values to verify homogeneity and a histogram of the residuals for normality based on the regular fixed-effects linear model (Figure 12.4). Figure 12.4 shows that residuals do not symmetrically center around 0. There seems minor evidence of the histogram of the residuals being skewed to the right. The problem may be partially due to repeated observations for each individual over the sampling period. To simply observe that effect, we run separate models for each individual, where the independent variable is day of week and the dependent variable is the *ln* form of the number of daily trips. The 95 percent confidence intervals for the intercepts and slopes are shown in Figure 12.5. There exist substantial variations in the intercepts among individuals, and there are also apparent individual-to-individual variations in the slopes. It signals the existence of extra random effects in the data. Therefore, mixed-effects models are considered as more appropriate than traditional fixed-effects models.

Testing the number of categories

In our data, the number of trips ranges from 0 to 17 (16 is missing). Therefore for the mixed-effects ordered logit model, we can test different numbers of categories ranging from 2 to 17 with an increment of 1. The goodness of fit (measured by Nagelkerke R^2) of the mixed-effects ordered logit models with different numbers of categories of trips is shown in Table 12.4. The results indicate that the models produce similar Nagelkerke R^2 values and similar estimates of the coefficients. Models with categories from 7 to 16 have approximately the same Nagelkerke R^2 value which is slightly higher than the models with fewer categories. In addition, the number of days with more than 5 trips account for less than 3% of all days. It seems reasonable to select 7 categories $(0, 1, 2, ..., 5, >5)$ by combining more than 6 daily trips as one category.

Comparing Poisson and negative binomial

Regarding the choice of the Poisson and negative binomial structures, if the mean of the dependent variable equals the variance, then the Poisson model is preferred. But if the variance is greater than the mean, negative binomial would be a better fit. We compare the goodness of fit of the Poisson model and negative binomial model for our data. The test used is the likelihood-ratio Chi-squared test where the null hypothesis is that the dispersion parameter equals 0.[16] We run the mixed-effects negative binomial model and obtain its log likelihood value ($LL_{nb} = -8361.32$). Then the mixed-effects Poisson model is examined and its log likelihood value is also recorded ($LL_p = -8567.505$). The next step is to calculate $\chi^2 = -2(LL_p - LL_{nb}) = 33.72$. Its p-value is smaller than 0.01 for df = 1. The large test statistic suggests that the count data are over-dispersed and cannot be sufficiently described by the Poisson distribution. Therefore the mixed-effects negative binomial model is deemed as a better fit.

[16] (Cameron and Trivedi 1998).

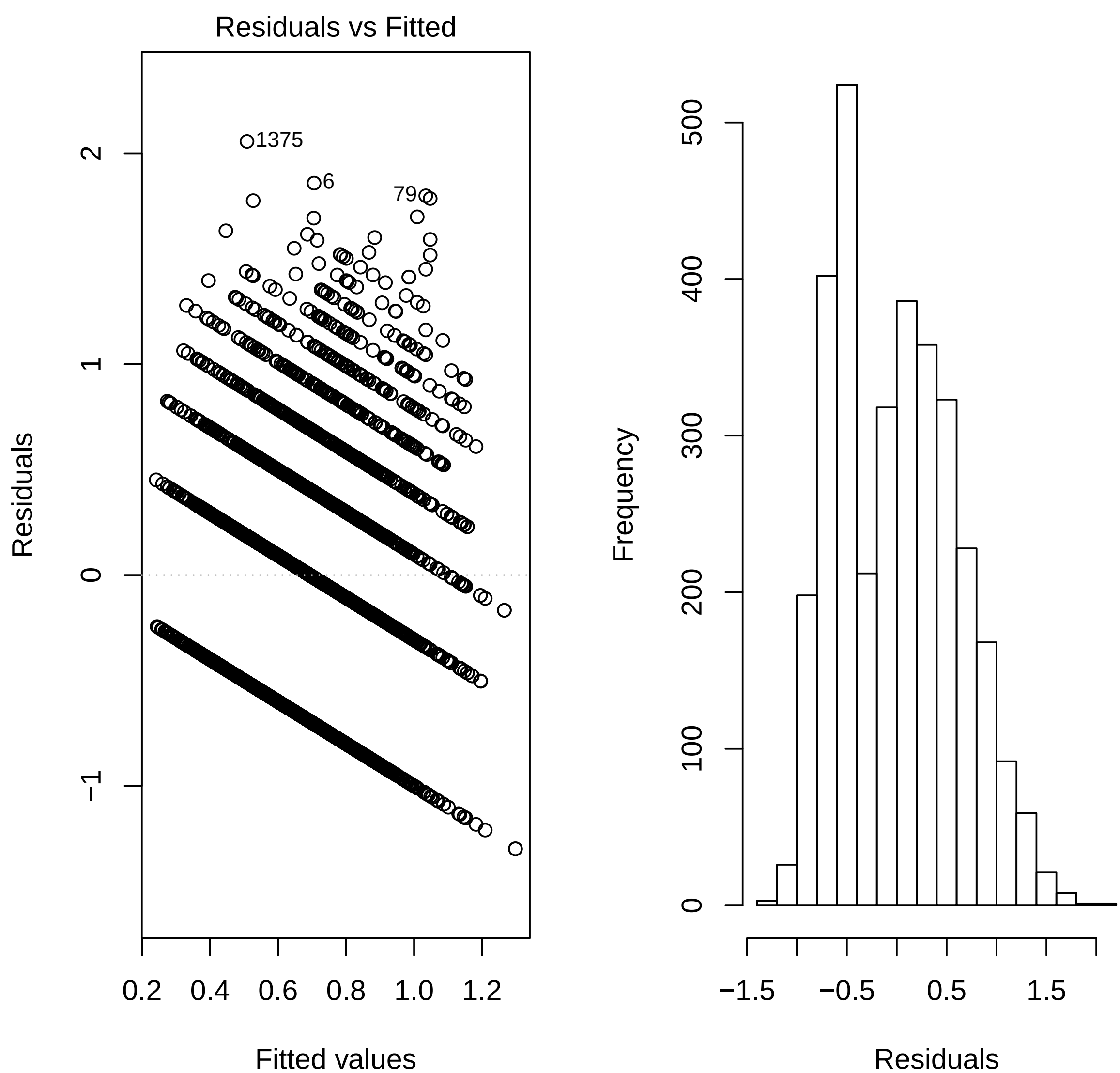


Figure 12.4: Residual plots of the fixed-effects linear model

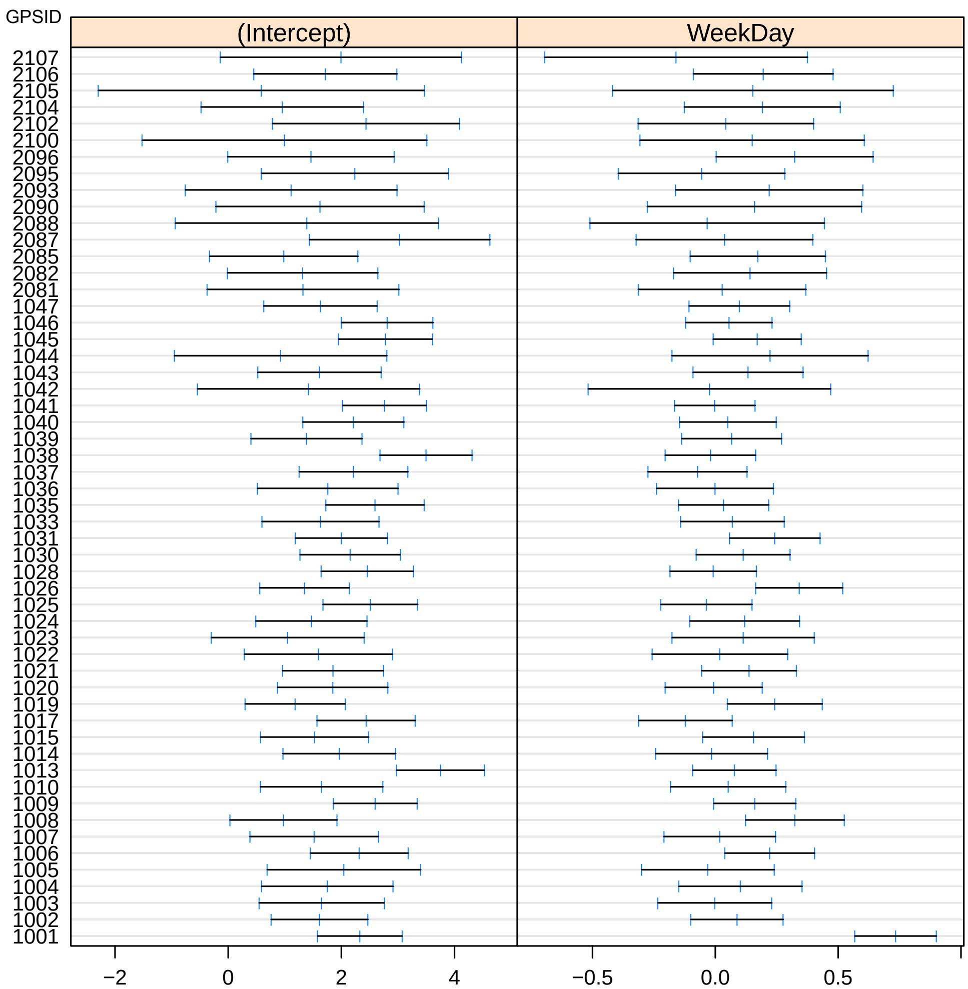


Figure 12.5: Confidence intervals (95 percent) for the intercepts and slopes of the individual-based regressions of the number of daily trips on the day-of-week variable

Table 12.4: Comparison of the goodness of fit for selecting the number of categories of trips for the mixed-effects ordered logit model

Categories of trips	Nagelkerke R^2
17	0.20
16	0.20
15	0.20
14	0.20
13	0.20
12	0.20
11	0.20
10	0.20
9	0.20
8	0.20
7	0.20
6	0.19
5	0.19
4	0.19
3	0.18
2	0.14

Modeling results

Table 12.5 exhibits the results from mixed-effects linear, mixed-effects log linear, mixed-effects negative binomial, and mixed-effects ordered logit, and mixed-effects zero-inflated negative binomial (ZINB) models. All models are estimated using the maximum-likelihood method. For the mixed-effects linear model, a one-unit increase in the independent variable can be interpreted as one more trip. For the mixed-effects log linear model, a one-unit increase in the independent variable can be interpreted as about 1% more trip. For mixed-effects negative binomial, ordered logit, and ZINB models, a one-unit rise in the independent variable can be interpreted as a one-unit increase in the log-odds of the number of trips.

Among the built environment variables, most entropy measures in various zones from home are negative, but only the entropy measures in the $[10, 15)$ min zone and $[15, 20)$ min zone are statistically significant. The results imply that greater diversity of services in these zones supports multi-purpose trip behavior and thus may help lower the number of trips. Interestingly, most access measures are not statistically significant except access in the $[15, 20)$ min zone from home. There are three possible reasons for explaining this:

1. This result may be due to its correlation with other land use variables, especially with the entropy measure (diversity of services) in the same zone.

2. The positive coefficient may suggest that more services in the $[15, 20)$ min zone, all else equal, induce a higher travel demand.

3. The above two reasons jointly contribute to the result.

We test several alternative models by including one land use variable at a time. The results show that none of the access measures in any of the zones are statistically significant. Therefore there is not enough evidence to support Reason (2) and Reason (3). Overall, the results from all the models show that land use variables in the $[0, 5)$ and $[5, 10)$ min zones from home do not appear to impact trip generation with sufficient statistical significance. Only the diversity of services in the $[10, 15)$ min and $[15, 20)$ min zones

Variable		Linear		Log-linear Binomial		Negative logit		Ordered		ZINB	
Land use	$A_{[0,5)}$	0.006		0.04		0.03		0.002		-0.02	
	$A_{[5,10)}$	-0.18		-0.20		-0.06		-0.22	0.006		
	$A_{[10,15)}$	0.16		0.15		0.09		0.27		0.06	
	$A_{[15,20)}$	1.13	*	1.07	*	0.80	*	1.24	*	0.48	*
	$H_{[0,5)}$	-0.34		-0.27		-0.29		-0.27		-0.46	
	$H_{[5,10)}$	0.58		0.11		-0.03		0.23		0.62	
	$H_{[10,15)}$	-7.55	***	-7.53	***	-5.85	***	-9.52	***	-3.10	**
	$H_{[15,20)}$	-2.70		-1.82		-2.97	**	-3.32		-1.95	
Day of week	Tue	0.003		-0.01		-0.01		0.003		0.01	
	Wed	0.02		0.02		0.02		0.02		0.03	
	Thur	0.05		0.07		0.05		0.09		-0.002	
	Fri	0.45	***	0.43		0.31	***	0.54	***	0.24	**
	Sat	0.95	***	0.73		0.57	***	0.98	***	0.53	***
	Sun	0.13		0.07		0.13	***	0.14	***	0.15	**
Month	Sep	0.28	***	0.48	***	0.18	***	0.47	***	0.13	***
	Oct	0.18	***	0.29	***	0.09	***	0.29	***	0.08	***
	Nov	0.24	***	0.26	***	-0.13	***	0.28	***	0.12	***
Socio-demographics	Age	-0.02	*	-0.01		-0.01	***	-0.02	***	-0.01	***
	Inc level 2	-0.36	***	-0.24		0.20	***	-0.32	*	-0.18	*
	Inc level 3	-0.52		-0.34		-0.27	***	-0.50	*	-0.27	
	Male	0.10		0.19		0.12		0.20		0.04	
Goodness of fit	log likelihood	-9,636		-9,754		-8,056		-11,033		-8,005	
	McFadden's R^2	0.05		0.04		0.06		0.05		0.06	
	Cox&Snell R^2	0.20		0.15		0.19		0.22		0.20	
	Nagelkerke R^2	0.20		0.15		0.19		0.22		0.20	
No. of observations		4,988									

Inc level 1: $< \$100,000$; Inc level 2: $\$100,000 - \$149,999$; Inc level 3: $> \$149,999$
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 12.5: Regression results for different mixed-effects model structures

can help decrease the number of daily trips. This finding may be due to that most of the subjects live in the suburbs which have relatively low access and low diversity of services, and their major non-work activities may be more likely to happen in the $[10, 20)$ min area from home.

The Pearson correlation test of key land use parameters are conducted (Table 12.7). access in the $[0, 5)$ min zone is highly correlated with the entropy measure in the same zone (the coefficient equals 0.74). As travel time from home rises, while there still exist positive correlations between access and entropy in the same zone, the level of correlation shrinks. For example, access and entropy in the $[15, 20)$ min zone only equals 0.13. In addition, there exist correlations for the same variable in different zones, and adjacent zones have higher correlation coefficients than zones that

are farther away from each other. For instance, the correlation between access in the $[0, 5)$ min zone and $[5, 10)$ min zone equals 0.69, while the correlation between access in the $[0, 5)$ min zone and $[10, 15)$ min zone equals 0.52 and the correlation between access in the $[0, 5)$ min zone and $[15, 20)$ min zone equals 0.46. Similar results can be found for other parameters. Geographical proximity contributes to the similarity of land use.

Regarding day-of-week variables, all else equal, Friday, Saturday, and Sundays are associated with more daily trips than other weekdays. Higher income, all else equal, seems to be associated with fewer trips. Limited time budgets for higher-income families may have played a role here. But more information about household structure would be helpful for further providing insights.

Table 12.6 shows the estimated coefficients for predicting the probability of zero trips from the mixed-effects ZINB model. Thursday, Friday, and Saturday are less likely to have 0 trips than Monday. The individual-specific random term in this equation is assumed to follow a normal distribution with mean zero. Its standard deviation is estimated as 0.30 which is statistically significant, another sign of the existence of extra random effects.

Table 12.6: Coefficients for predicting the probability of zero trips for the mixed-effects ZINB model (using Monday as the base term)

Variable	Estimate
Sunday	0.19
Tuesday	0.12
Wednesday	0.15
Thursday	-0.40
Friday	-0.49
Saturday	-0.34
St. dev (random term)	0.30

Model fit

As these models have different structures, there is no direct measure for comparing these models' goodness of fit to the classic R^2 in ordinary least squared regressions. It is also invalid to compare the log likelihood values across different model structures. To shed more light on this issue, we calculate several Pseudo-R^2 measures which are based on comparing the log likelihoods of the model with a null model: McFadden's Pseudo-R^2, Cox&Snell R^2, and Nagelkerke R^2. As shown in Table 12.5, the five models have close Pseudo-R^2 values, though they are not ranked quite the same in terms of these Pseudo-R^2 measures. Overall, the mixed-effects ordered logistic model seems to be in the first tier because it displays higher goodness of fitness than other models in most measures. The mixed-effects ZINB, NB, and linear models are about in the second tier. The log linear model has the lowest Pseudo-R^2 estimates for all measures. Note that since all the models have close Pseudo-R^2 values, further investigation is needed to gain more insights about the models' predictability.

Table 12.7: Correlation of access (A) and diversity (H) of services in $[5, 10)$ min, $[10, 15)$ min and $[15, 20)$ min driving zones around home

	$A_{[0,5)}$	$A_{[5,10)}$	$A_{[10,15)}$	$A_{[15,20)}$	$H_{[0,5)}$	$H_{[5,10)}$	$H_{[10,15)}$	$H_{[15,20)}$
$A_{[0,5)}$	1.0	0.69	0.52	0.46	0.74	0.40	0.14	0.32
$A_{[5,10)}$		1.0	0.78	0.66	0.50	0.42	0.35	0.24
$A_{[10,15)}$			1.0	0.70	0.29	0.49	0.41	0.21
$A_{[15,20)}$				1.0	0.34	0.47	0.54	0.13
$H_{[0,5)}$					1.0	0.57	-0.03	0.04
$H_{[5,10)}$						1.0	0.16	-0.20
$H_{[10,15)}$							1.0	-0.23
$H_{[15,20)}$								1.0

Note: All estimated coefficients are statistically significant at the 1% level.

Predictive results

The five estimated mixed-effects models (linear, log linear, negative binomial, ordered logit, and ZINB) are employed to predict trip generation patterns at the macroscopic level. In the mixed-effects ordered logit model, for every trip, we calculate the probability of choosing each trip level $(0, 1, 2, ..., 5, >5)$. Based on the probability of each trip level, we randomly generate a choice for every trip, based on which the predicted trip counts for all trip levels can be calculated. This process is repeated for 100 times, and the average trip frequency for each trip level is computed. For the other four models, we use the 0.5 cutoff points as the threshold. For example, if the predicted value is below 0.5, it is considered as 0 trips. If the predicted value is within $[0.5, 1.0)$, it is considered as 1 trip. If the predicted value is within $[1.5, 2.5)$, it is considered as 2 trips.

Figure 12.6 shows the observed and predicted trip counts. Several observations can be made:

1. The mixed-effects ordered logit model outperforms other models by matching the actual observations the best for all numbers of daily trips.

2. The mixed-effects log linear model over-predicts the number of days with 0 or 1 trips while under-predicting the number of days with more than 1 trip.

3. The mixed-effects log linear, NB, and ZINB models over-estimate the number of days with 1 or 2 trips but considerably under-estimate the number of days with 0 trips.

Model	MAE	MAPE (%)
Mixed-effects ordered logit	6.71	1
Mixed-effects log linear	434.86	77
Mixed-effects linear	597.14	73
Mixed-effects ZINB	635.43	75
Mixed-effects negative binomial	647.71	76

Table 12.8: Model mean average error (MAE) and mean average percentage error (MAPE)

The mean absolute error (MAE) measure and the mean absolute percentage error (MAPE) for each model are calculated. Mathematically, the equation for calculating MAE can be written as:

$$MAE = \frac{1}{N} \sum_{n=1}^{N} |y_n - f_n| \tag{12.12}$$

And the equation for computing MAPE can be expressed as:

$$MAPE = \frac{1}{N} \sum_{n=1}^{N} \left| \frac{y_n - f_n}{y_n} \right| \times 100\% \tag{12.13}$$

Where y_n is the actual value for the nth observation in the data and f_n is the predicted value. N is the total number of observations in the data. The MAE is an average of the absolute errors and the MAPE is an average of the percentages of the absolute errors. The smaller MAE/MAPE is, the more accurate the predicted values are. The five models' MAE and MAPE values are reported in Table 12.8. The mixed-effects ordered logit model obviously produces the lowest MAE and MAPE values, which supports visual observation from Figure 12.6. Interestingly, based on the MAE measure, the mixed-effects log linear model ranks the second; nevertheless, its rank drops to the lowest according to the MAPE measure. The mixed-effects ZINB model ranks higher than the mixed-effects NB model for both measures.

Conclusions

Trip generation is typically modeled with fixed-effects models. For data sets such as the GPS travel data that feature repetitive observations among individuals, traditional fixed-effects models do not fit well. Furthermore, there is a lack of research on comparing various alternative model structures on modeling count data with repetitive observations. To this end, this chapter conducts a comparative study of five mixed-effects model structures based on

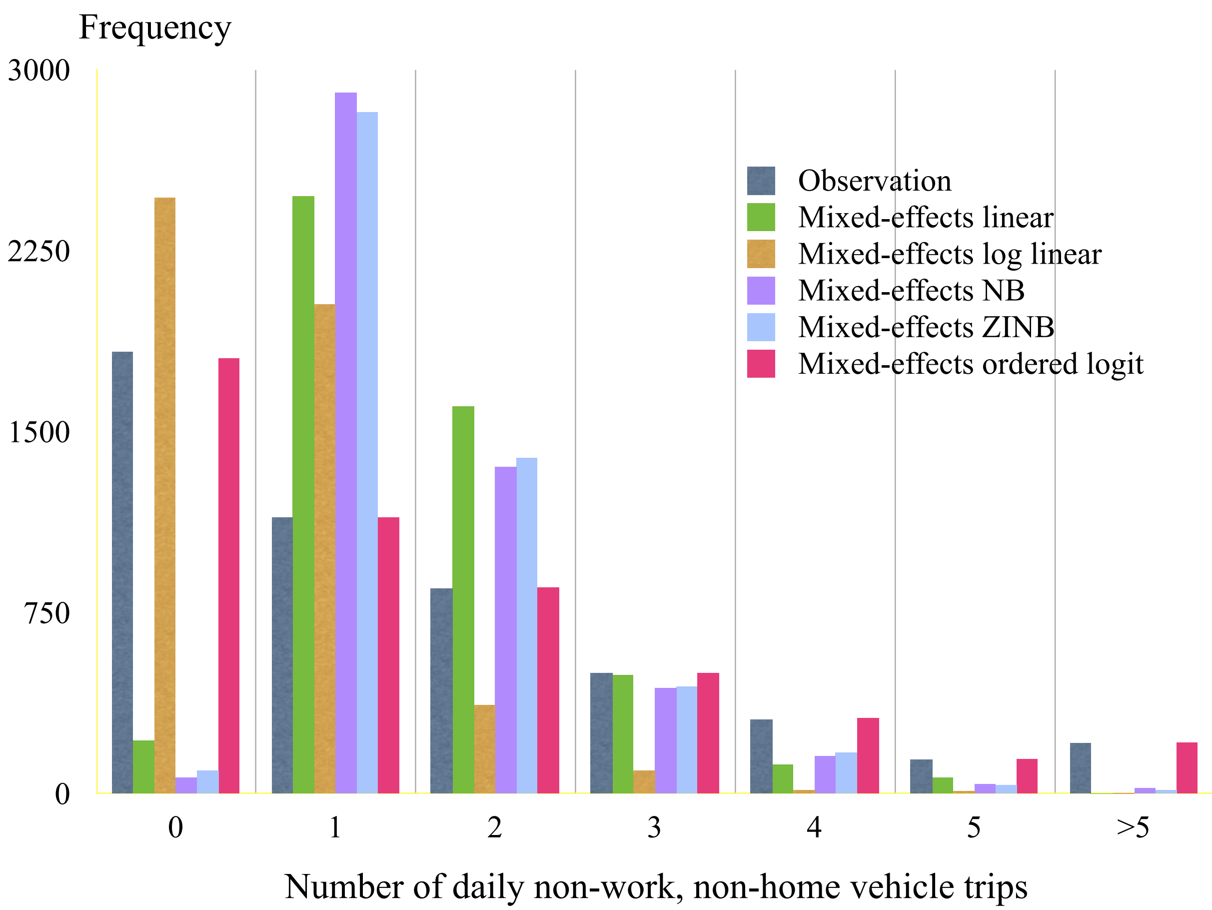


Figure 12.6: Predicted and observed non-work, non-home vehicle trip patterns

the in-vehicle GPS data. This chapter uses the parcel-level land use data around home to examine the relationship between land use and non-work vehicle trip generation. The key findings are:

1. The mixed-effects ordered logistic model produces the highest goodness of fit of all the models tested.[17] The results indicate that traditional Poisson/NB models may not be the best choice for modeling tip generation using the GPS data.

2. The access measures in the $[0,5)$ min, $[5,10)$ min, $[1015)$ min, and $[15,20)$ min driving zones from home are not found to influence the generation of non-work vehicle trips for our data with sufficient statistical significance. Based on our hypothesis, access may both induce and dampen the generation of non-work

[17] This finding is consistent with Lim and Srinivasan (2011) though the models tested in that paper are all fixed-effects models.

vehicle trips. It is likely that both positive and negative effects may have played a role here. The correlation among access measures in adjacent zones also influence the estimates.

3. The diversity of services in the $[10, 15)$ min, and $[15, 20)$ min driving zones from home displays depressive effect on the number of non-work, non-home vehicle trips, a sign of trip chaining behavior. Most of the subjects in this chapter live in the suburbs. Our findings reflect non-work driving behavior for individuals living in the suburbs where land use in the immediate vicinity of home is frequently less diverse than zones which are more than 10 minutes away.

Next

This chapter can be expanded by further examining vehicle trip generation for various non-work trip purposes, as the effects of land use on trip generation for different purposes may well be different. It is of interest to investigate such effects at the microscopic level.

13
Job Access and Spatial Equity of a Toll Road

I Gusti Ayu Andani, Lissy La Paix, Shanty Rachmat,
Ibnu Syabri, and Karst Geurs

Abstract: This chapter describes an evaluation of the job access and spatial equity impacts of the Cipularang toll road in the Jakarta – Bandung corridor in Indonesia, which was constructed in 2005. An ArcGIS, transport demand model extension, is used to obtain travel time and generalised cost estimates. The potential access measure and Shen access index are used to measure access with and without job competition. Spatial equity is examined based on the access measures using the Gini coefficient, Palma ratio, and a two-step cluster analysis. The analysis shows that the construction of the Cipularang toll road has reduced travel time in the whole region by 13% and potential job access increased by 5%. However, the toll road also increases job competition as more workers can access jobs available in the job-poor area in between Jakarta and Bandung, resulting in a small decrease in the number of accessible jobs per worker. This chapter concludes that the construction of the toll road has no impact on spatial equity as measured by the Gini coefficient and the Palma ratio.

Introduction

Keywords: Access; Equity; Employment; Job competition; Toll road

Access metrics estimating the number of activities that can be reached within a certain area are often used in spatial equity analysis as they are able to capture the quality of transport infrastructure and the spatial distribution of the activities (land use).[1] However, applications of access metrics in ex-post evaluations of road investments are rare, in particular for developing countries.

[1] (Geurs and Van Wee 2004).

A new road can have diverse equity impacts, ranging from access to social opportunities to regional economic developments. A particular example is the construction of toll roads, which allow users to have a typical choice between a quicker but expensive route and a slower but inexpensive route. The additional costs and changes in travel time can be unevenly distributed across a population, according to socioeconomic level. There can even be groups for which the new road has detrimental effects. For example, high-income commuters in Cape Town, South Africa are more likely to benefit from toll roads whereas lower-income commuters choose alternative non-tolled routes.[2]

[2] (van Dijk et al. 2015).

This chapter presents an ex-post evaluation of the impact of a toll road on job access and spatial equity in a developing country context. We used an ArcGIS, transport demand model extension, to estimate the transport impacts of the introduction of the Cipularang toll road in the Jakarta – Bandung corridor in Indonesia.

The Cipularang toll road links two major Indonesian cities, Jakarta, and Bandung. In 2004, 78.3 million passengers passed through the Jakarta - Bandung corridor, making it one of the busiest passenger transport routes in Indonesia. The distance between the cities is about 180 km and the modal split is dominated by car traffic.[3] Empirical evidence also suggests that the introduction of this toll road corridor induced positive responses from the real estate market.[4]

[3] (Lubis et al. 2005).

[4] (Dorodjatoen 2009).

In the Indonesian context, ex-post evaluation of transport infrastructure investments, as in many countries across the globe, has not yet received much attention. Ideally, transport policy should follow the decision-making cycle,[5] in which, needs or rationales are identified first to define the objectives or the desired transport system or system level. Then, an ex-ante evaluation (appraisal) is conducted to identify possible transport policies or projects. Subsequent steps (monitoring, ex-post evaluation and feedback) after the policy has been implemented are often neglected. An ex-post analysis is important as investigating past successes and failures improves the quality of appraisal for upcoming projects and enhances accountability. Many countries require ex-post evaluation of transport projects, however, few actually enforce this requirement, and this failure is often related to a lack of dedicated funding fur such evaluations and limited availability of relevant data.[6]

[5] (Emberger et al. 2008).

[6] (Worsley 2017).

Questions

This chapter addresses the following question:

- What is the impact of the toll road on job access and spatial equity?

Given the importance of toll roads in the development of the major road network in Indonesia, this chapter focuses on the ex-post evaluation of the Cipularang toll road. This chapter conducts an empirical calculation of several access measures to distinguish between the effects on jobs and working population distribution. The Gini coefficient, Palma ratio, and a two-step cluster method are also applied to gain insight into the distribution of the impacts on job access across the region.

Methods

To assess the impact of the Cipularang toll road on access and spatial equity, we applied three stages of analysis in this chapter. Firstly, we created an ArcGIS transport network, then the 4-step transport model extension Traffic Analyst for ArcGIS[7] was used and calibrated to produce traffic flows, travel time and generalised cost matrices in a scenario with and without the toll road. Next, we developed a 24-hour traffic simulation, which included the toll road. The use of the transport demand model enabled us to consider congestion effects by adding capacity restraints in the traffic model. We employed road network data from OSM[8] as it provided road network data up to the local level. Applying four-step models is challenging because of data limitations. It is important to note as well that our model aimed to predict travel times in the Jakarta-Bandung region and, specifically, traffic flow on the corridor of the Cipularang toll road, thus we ignored traffic on other roads.

Secondly, we calculated access indicators by using the generated travel time and cost matrices, considering the number of jobs and the size of the working population. Thirdly, we conducted a spatial equity analysis based on the equity indices (Gini coefficient and Palma ratio) and spatial distribution of access among districts with a two-step cluster method. The unit of analysis in this chapter is districts in the study area.

[7] (Rapidis 2018).

[8] (OpenStreetMap contributors 2016).

Traffic simulation

The traffic simulation was conducted through the conventional 4-step model. Firstly, a number of trips were generated in each district by considering the population size and the proportion of residential area as production parameters and the number of jobs and the proportion of industrial and commercial areas as attraction parameters. The parameters were estimated from a regression analysis using population and land use data from the Jakarta metropolitan area.[9]

[9] (JICA 2004).

In the second phase, the balanced-generated trips were distributed using the Furness method. This method also used a deterrence function, which was calculated from the gravity parameter and road traffic cost matrix. The gravity parameter assumes that a higher travel time will result in fewer trips made. We calculated it from the Indonesian labour force travel survey that mapped the mobility of labour forces in the study area in 2015.[10]

[10] (BPS 2015).

Furthermore, road traffic cost was calculated from generalised cost considering the travel time between districts (using Google Maps API), fuel cost for each type of vehicle and value of time. The value of time was derived from a stated choice experiment survey conducted in the Jakarta-Bandung region for 1,600 respondents.[11] Next, a growth factor forecasting calculation (Furness method) was performed on the balanced generated trips and converted into an origin-destination (OD) matrix.

[11] See (Andani et al. 2021) for more details about this experiment.

In the third phase, OD matrices for three modes were estimated (car, heavy vehicle, and motorcycle), using the proportion of mode share in the area. Lastly, the road traffic assignment was carried out, assigning the generated OD matrix to the road network. A user equilibrium algorithm was used in this assignment. This last step produced the best travel route, the amount of traffic and the costs (travel time, distance, and generalised cost) for the pair of zones.

Access measurements

Access, is defined as the potential of opportunities for interaction.[12] There are many definitions afterwards. On the basis of a large number of studies,[13] were able to distinguish four main elements to define access: transport, land use, temporal, and individual components. Access measures can be also categorised into: (1) infrastructure-based access, (2) location-based access, (3) person-based access, and (4) utility-based.[14]

[12] (Hansen 1959).

[13] (Geurs and Van Wee 2004).

[14] See more details in (Geurs and Van Wee 2004).

In this chapter, we applied infrastructure-based measures to assess the performance of the road network as well as location-based measures. The infrastructure-based measure focuses on the performance or service level of transport infrastructures, such as the length of infrastructure networks, level of congestion and average travel speed on the road network. It is worth noting that estimating travel time without considering capacity restraints and traffic flow will result in underestimation. Hence, several researchers also developed a traffic model to evaluate road infrastructure investment.[15]

[15] For example (van Dijk et al. 2015, Xiong et al. 2015).

Furthermore, we estimated two access measures. Firstly, the standard job potential access measure was calculated by weighting opportunities in a certain area by using an attribute of attraction (population, facilities, etc.) and a measure of impedance (distance, travel time, cost). Secondly, the Shen access index was estimated to incorporate the spatial distribution of jobs and the working population competing for these jobs.[16] Thus, we evaluated the combined effects of transport elements and job distribution, augmented by the inclusion of congestion and competition effects.

[16] (Shen 1998).

Average travel time and generalised cost Average travel time and generalised cost $\overline{c_r}$ were calculated by summing up the travel time or generalised costs for all the trips from one origin (i) in situations with the Cipularang toll road ($r = 1$) and without it ($r = 0$), and then dividing this by the total amount of trips possible (n) from that origin.

$$\overline{c_r} = \frac{\sum_i c_{i,r}}{n_{c_{i,r}}} \tag{13.1}$$

The monetary cost in the link was determined from the generalised cost, taking into account fuel cost and value of time (V_t).

The generalised cost in link l ($C_{g,l}$) was calculated using the following formula:

$$C_{g,l} = C_{f,l} \cdot d_l + C_{\tau,l} \cdot d_l + C_{t,l} \cdot V_t \tag{13.2}$$

where $C_{f,l}$ is fuel cost (IDR per kilometre), d_l is the length of the link (in kilometre), $C_{\tau,l}$ is toll cost (IDR per kilometre), $C_{t,l}$ is travel time (hour), and V_t is the value of time (IDR per hour). A list of all variables can be seen in Table 13.3.

Table 13.1: Goodness of fit (R^2) of fitted distribution functions

Impedance	Distribution function			
	Log-logistic	Gaussian	Negative exponential	Power
Time	1.00	0.99	0.99	0.86
Generalised cost	1.00	1.00	0.97	0.77

Potential job access Job access denotes the ease that spatially distributed jobs can be reached from a given location. The most used potential access measure is based on Hansen's access formula,[17] as follows:

[17] (Hansen 1959).

$$S_{i,r} = \sum_j E_j \cdot f(c_{ij,r}) \tag{13.3}$$

Here, S_i is the access for location i with toll road (r=1) or without (r=0), E_j is the number of relevant jobs in location j, c_{ijr} is the cost (i.e. travel time or generalised cost) of a trip from i to j with toll road ($r = 1$) or without ($r = 0$), and $f(c_{ijr})$ is the cost decay function measuring the spatial separation between locations i and j.

The cost decay function reflects the friction in connecting zones i and j in the network and is negatively correlated with the attractiveness of the destination (i.e. jobs). The access results, therefore, are profoundly affected by the decay function. Various types of cost decay were tested for the access analysis such as negative power, negative exponential, Log-logistic and the Gaussian specification (see the comparison in Table 13.1 and Figure 13.1). Note that the power function is not depicted in Figure 13.1 as the probability value is very low. Regarding the impedance parameter based on the household survey data, we found that the log-logistic cost decay function (Equation 13.4) produced the best fit with the travel data.

The log-logistic cost decay function is specified as:

$$f(c_{ij}) = [1 + exp(a + b \cdot ln(c_{ij}))]^{-1} \tag{13.4}$$

where a and b are parameters to be estimated. We estimated the parameters of separate log-logistic functions for both time and generalised cost (Table 13.2).

Potential job access with impedance function and competition (Shen index)

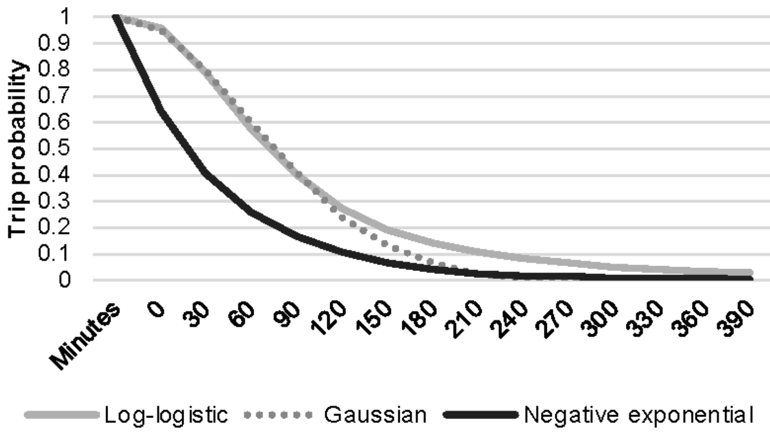


Figure 13.1: Net auto vs. net transit access to all jobs via auto within 30 minutes

To improve these access measures, we considered competition in the access measurement by including the potential demand for jobs. Potential job access measures the number of jobs within reach of a resident from an origin within a certain travel distance (potential supply) divided by the potential number of residents within reach of the same destination (potential demand).[18] The Shen index is similar to the two-step floating catching area (2SFCA) method used in geography[19] to access spatial access to health care. Several authors enhanced the 2SFCA method by for example incorporating distance decay.[20] In this chapter, we refer to this access measure as the 'Shen index.' If the Shen index is 1, then the number of jobs is proportional to the size of the working population. It can be calculated with the following formula:

Table 13.2: Parameters for log-logistic cost-decay function

Impedance	a	b
Travel time (C_t)	-11.55	2.50
Generalised cost (C_g)	-11.71	2.10

[18] (Shen 1998).

[19] (Radke and Mu 2000).

[20] e.g., (Luo and Wang 2003).

$$A_{ir} = \sum_j \frac{f(c_{ij,r})}{D_j}, D_{jr} = \sum_k L_k f(c_{kj,r}) \tag{13.5}$$

Here, A_i is the Shen Index or the ratio between the potential job access of people living in location i, with toll road (r=1) or without (r=0) and the number of people seeking job opportunities in location j (D_j), E_j is the number of relevant jobs in location j, is, L_k is the number of the working population in the study area, and $f(c_{kjr})$) is the impedance function measure the spatial separation between k and j, with toll road ($r = 1$) or without ($r = 0$).

This chapter used data collected from the Indonesian database for policy and economic research[21] to calculate job access. We used

[21] (WorldBank 2018).

Table 13.3: List of variables

Notation	Description
c	Cost (i.e. Travel time or generalised cost) of a trip
C_g	Generalised cost (IDR)
C_f	Fuel cost (IDR per kilometer)
d	The length of the link (in kilometer)
C_τ	Toll cost (IDR per kilometer)
C_t	Travel time (hour)
V_t	Value of time (IDR per hour)
S	Potential access of a location
E	Number of relevant jobs in a certain location
A	Shen Index (the ratio between the potential jobs access and the number of people seeking job opportunities)
D	People seeking job opportunities
L_k	Working population in the study area
l	Link in the network
r	Existence of a toll road [1,0]
i	Origin of a trip
j	Destination of a trip

employment data as a proxy for the number of jobs in the study area and defined employed people as persons who worked for pay or assisted others in obtaining pay or profit for at least one hour during the survey week. In addition, we used labour force data to calculate the number of job seekers in the study area. In this context, 'labour force' is defined as persons 15 years old and older who are working, are temporarily absent from work but had jobs, or who do not have work and are looking for work.[22] This way, we exclude people of working age who are in schools, doing housekeeping, or not doing or looking for any profitable activity. This data is only available at the municipality level; to be able to conduct analyses at the district level, this data is extrapolated by using the population ratio. Note that due to data limitations, we were unable to distinguish between employed workers and job seekers and account for job types (e.g., by occupational class).[23]

[22] (BPS 2015).

[23] See (Smith et al. 2020).

Measuring spatial equity

access is normally used for equity analysis because it emphasises people and their interactions with places, and also captures both transport infrastructure and the spatial structure of the destinations (land use).[24] In the perspective of access, equity is commonly differentiated into spatial and social equity.[25] Spatial equity refers

[24] (Geurs and Van Wee 2004).

[25] (Van Wee and Geurs 2011).

to the geographical location of an individual, population group, or region, which is affected by an infrastructure project. Social equity is concerned with the impact of the infrastructure project on the economic or social condition of the individual, population group, or region. Since this chapter focuses on the geographical impacts of a toll road, spatial equity (i.e. its overall distribution, inequity at the extreme groups and whether job access is distributed evenly across the region) is addressed. To that end, we measured the Gini coefficient, Palma ratio, and the spatial distribution of access with a two-step cluster method.

Several statistical indicators can be used to assess the spatial equity implications of access impacts of road investments. A comprehensive study comparing various equity measures to assess the impact of road pricing policy concluded that using a single measure can lead to a biased evaluation.[26] The Gini coefficient,[27] which has been widely used to assess income inequity, is insensitive to any changes in measurement (scale-independent), which gives it a major advantage over other measures. The Gini coefficient also has been adopted to evaluate distributional impacts of access in some studies.[28]

[26] (Ramjerdi 2006).

[27] (Gini 1936).

[28] (Lucas et al. 2016, Pritchard et al. 2019, Van Wee and Geurs 2011).

The Gini coefficient is commonly used to measure the distribution of income. It is a value between 0 and 1, where 0 is perfect equity and 1 is perfect inequity. We calculated the Gini coefficient to compare access levels with and without the toll road. We estimated the coefficient by using the trapezoidal Lorenz curve approximation, depicting the (ranked) cumulative share of access against the cumulative share of the corresponding population by district across the Jakarta – Bandung region. A Gini coefficient of 0.5 says that there is high inequality, but says nothing about the distribution of that inequality.[29] Since income per capita data is not available, monthly expenditure per capita data is used in the analysis. The spatial distribution of monthly expenditure per capita across districts in the study area can be seen in Figure 13.3(left).

[29] (Banister 2018).

Complementary to the Gini index, we also explored the Palma ratio.[30] Originally, the Palma ratio depicts the ratio of income shares between the richest 10% and the poorest 40%. Palma observed that changes in income are almost exclusively due to the changes in the share of the richest 10% and poorest 40% because the middle-income group between the richest and the poorest always capture approximately 50% of gross national income. He pointed

[30] (Palma 2011).

out that the stability of income share of the middle is a consistent finding across different data sets, countries and time periods.

In this chapter, we calculate the Palma ratio to assess the inequity between the average access of the richest 10% districts and the poorest 40% districts.[31] A Palma ratio of 2.0 indicates that the top 10% (in terms of income) has twice the (job) access level as the lowest 40%. To account for the spatial distribution of job access, we clustered job access measures among districts in the study area by using a two-step cluster method in which the number of clusters was determined based on the minimum value of the Bayesian information criterion – BIC.[32] Cluster analysis is commonly used in transport and land use domain studies to create groups of areas with homogeneous access measures and land use characteristics. This method enabled us to identify the characteristics of districts that are likely to benefit from the new toll road and classify them based on the access impacts.

[31] Adopting methods from (Guzman and Oviedo 2018) and (Pritchard et al. 2019).

[32] (Schwarz 1978).

Several variables are also included to identify the characteristics of districts that are likely to benefit from the new toll road and classify them based on the access impacts. According to Chi,[33] the impact of a new highway differ across rural, suburban, and urban areas. A new toll implementation would affect each income population segment differently.[34] Therefore, in the cluster analysis, we considered variables of residential land use growth and monthly expenditure per capita (as a proxy to income) to classify the districts. Furthermore, as the focus of this chapter, distribution of jobs and working population are also included in the cluster analysis.

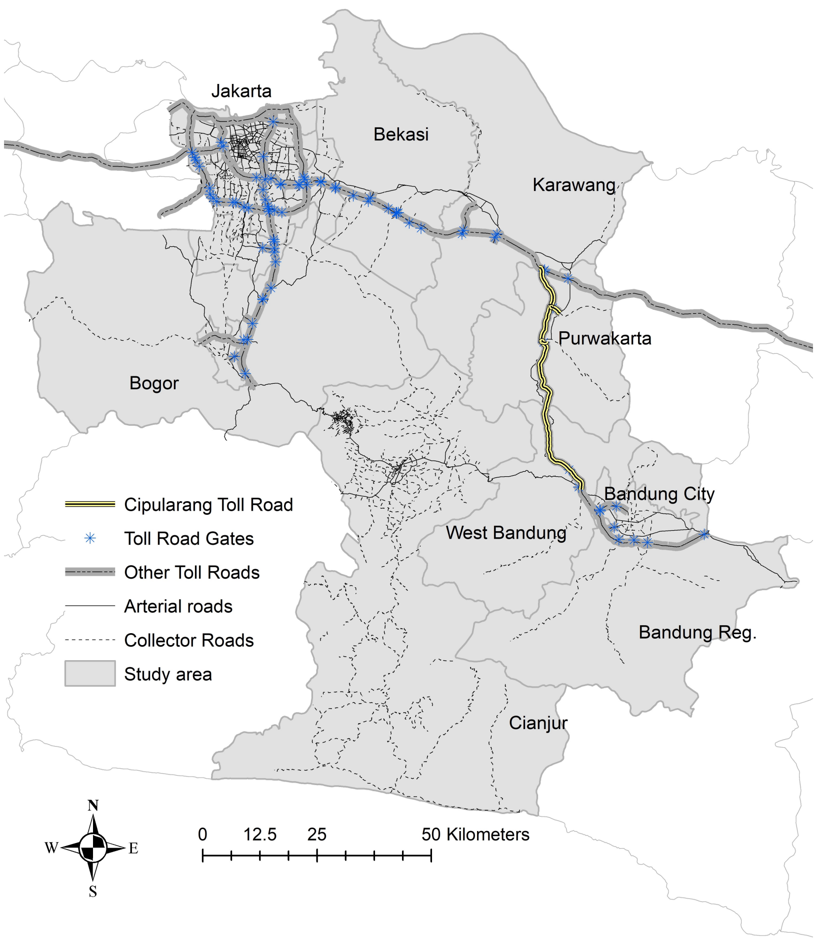
[33] (Chi 2012).

[34] (Di Ciommo and Lucas 2014, van Dijk et al. 2015).

Study area

The study area covers approximately 15,250 km2 in the corridor between Jakarta and Bandung as shown in Figure 13.2. The name 'Cipularang' is a contraction of 'Cikampek, Purwakarta and Padalarang.' This toll road connects Jakarta and Bandung by connecting the Jakarta-Cikampek toll road and the Padalarang-Cileunyi (Padaleunyi) toll road (of which the Pasteur toll road in Bandung is also a part). The Cipularang toll road has five gates; three gates are located in the West Bandung Regency , and the other two are in the Purwakarta Regency. The study area covers of 16 cities or regency and 229 districts.

Figure 13.2: Study area



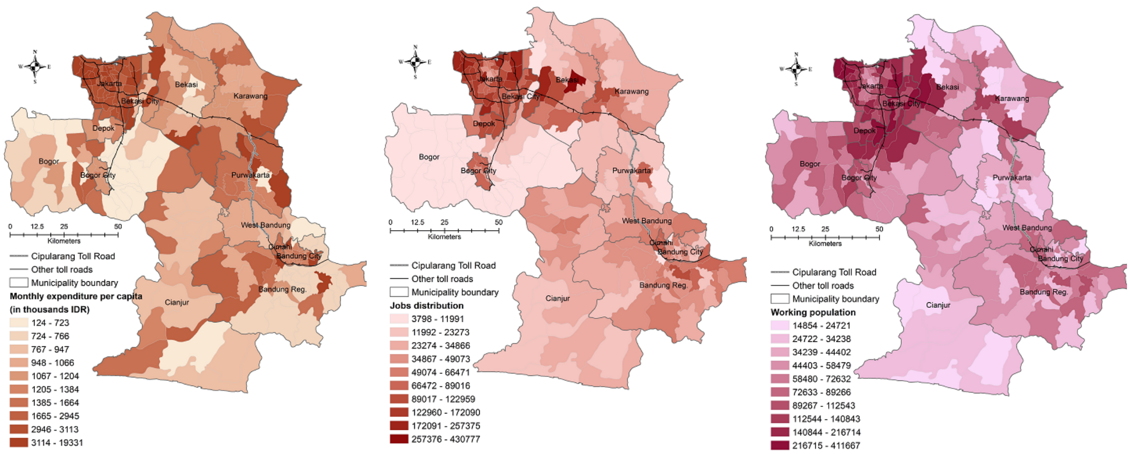


Figure 13.3: Spatial distribution of (left) monthly expenditure per capita, (center) jobs, and (right) working population

Between 2004 and 2013, residential land use increased by 2.5% and industrial land use by 1%.[35] The emergence of industrial and residential areas contributed to the increasing access, although jobs and the working population are still concentrated in the Jakarta and Bandung metropolitan area, as shown in Figure 13.3.

[35] Andani et al. 2019.

Findings

This section presents the results of the traffic simulation (average travel time and generalised cost), for potential job access and the spatial distribution of these values across the region.

Travel time estimation

Several performance measures were applied to evaluate the accuracy of the match between the observed travel time, derived from the Google Maps API, and simulated travel time. The value of the RMSPE is 9.7%, and the value of the correlation coefficient is 0.90. This indicates that the error is small enough and the accuracy of the model high enough to be able to predict travel time between origin-destination pairs. As Figure 13.4 shows, the model results show a similar pattern to the observed travel times. The estimated traffic flows on the Cipularang toll road are in line with the observed traffic data, with a percentage error of 3.7%. Figure 13.5 shows that without the Cipularang toll road, there is less traffic in

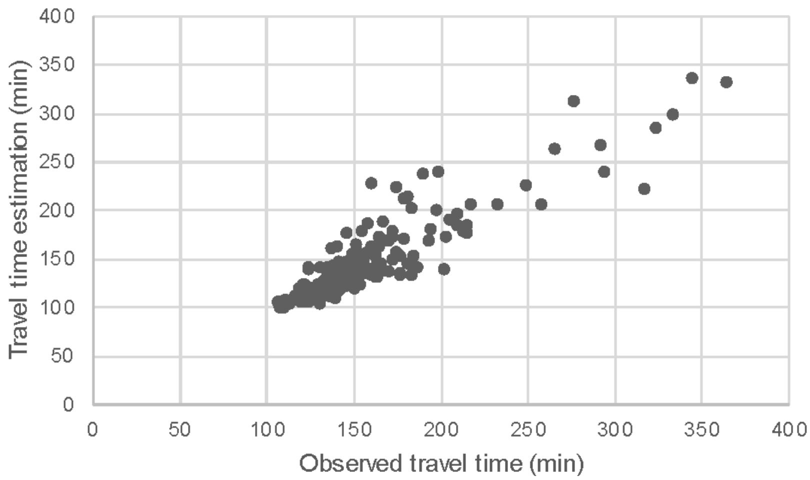


Figure 13.4: Comparison between observed and model results

Bandung and the northern part of this region. On the other hand, there is a significant increase in traffic on the other regional non-tolled roads.

The average travel time between districts was estimated to be 154 minutes, similar to the observed travel time obtained from Google Maps API (155 minutes). The most strongly impacted regions are in the corridor including the north-western area in Jakarta and the south-eastern region in Bandung (see Figure 13.6).

Regions in the west, such as Bogor and Cianjur, appear to be least affected by the development of the Cipularang toll road. Overall, weighted by the traffic flow, the Cipularang toll road has reduced the average travel time in the whole region by 13%; see Table 13.4. Several districts in Purwakarta experienced a weighted average travel time reduction up to 25%. This can be explained by the fact that this area contains two toll gates. It is also situated between two employment centres in the area: Jakarta and Bandung. This finding supports the observation that the impact of toll mostly occurs in the area alongside the toll road.[36]

[36] (Van Wee and Geurs 2011).

When we looked at specific origin-destination pairs, we found that the greatest reduction in travel time occurred between Cipendeuy (a district in the Bandung regency) and Teluk Jambe (a district in Karawang), which had almost 1.5 times greater travel times without the Cipularang toll road. The difference between the estimated average generalised cost with and without the toll road is not as great as the difference for the average travel time, given that

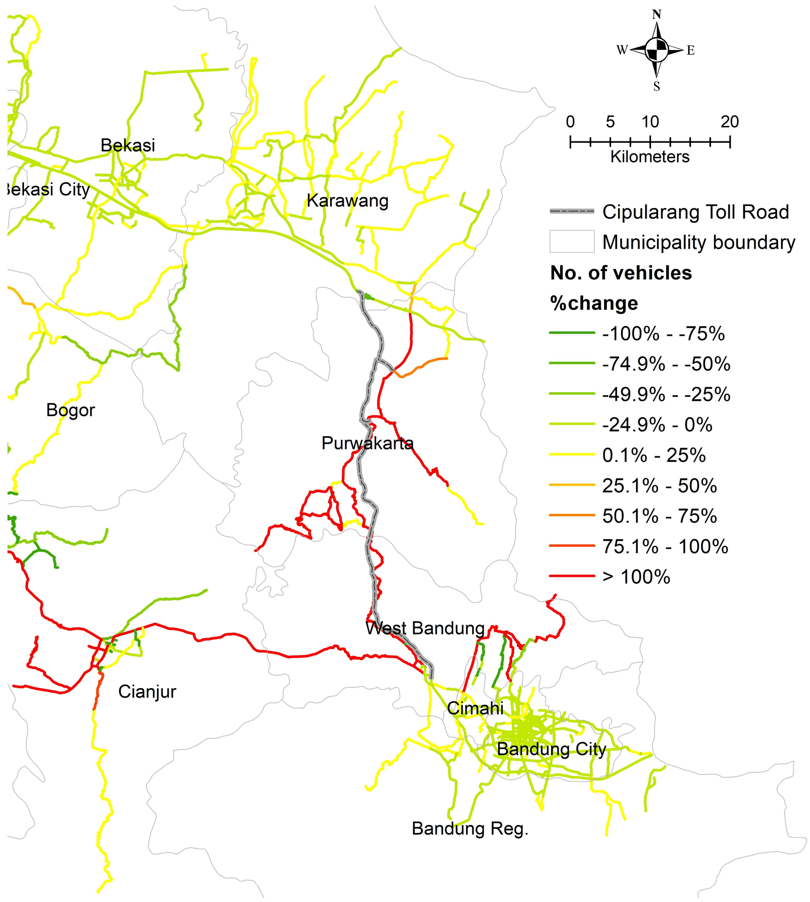


Figure 13.5: Changes in traffic flow without the Cipularang toll road

to use the toll road, users need to pay a fee, which increases the total travel cost. As observed from Figure 13.6, the estimated average travel time and generalised cost show a contrast between areas in the toll road corridor and areas at great distances from it.

Potential access measures

Table 13.5 presents the results of various access measures, weighted by the working population in each zone. access measures with time decay showed more significant changes than measures with generalised cost impedance. This indicates an overestimation of the impact as it is only taken into account the travel time. It is worth noting that the result of each access measures in this chapter is different from each other, though complementary to each other.

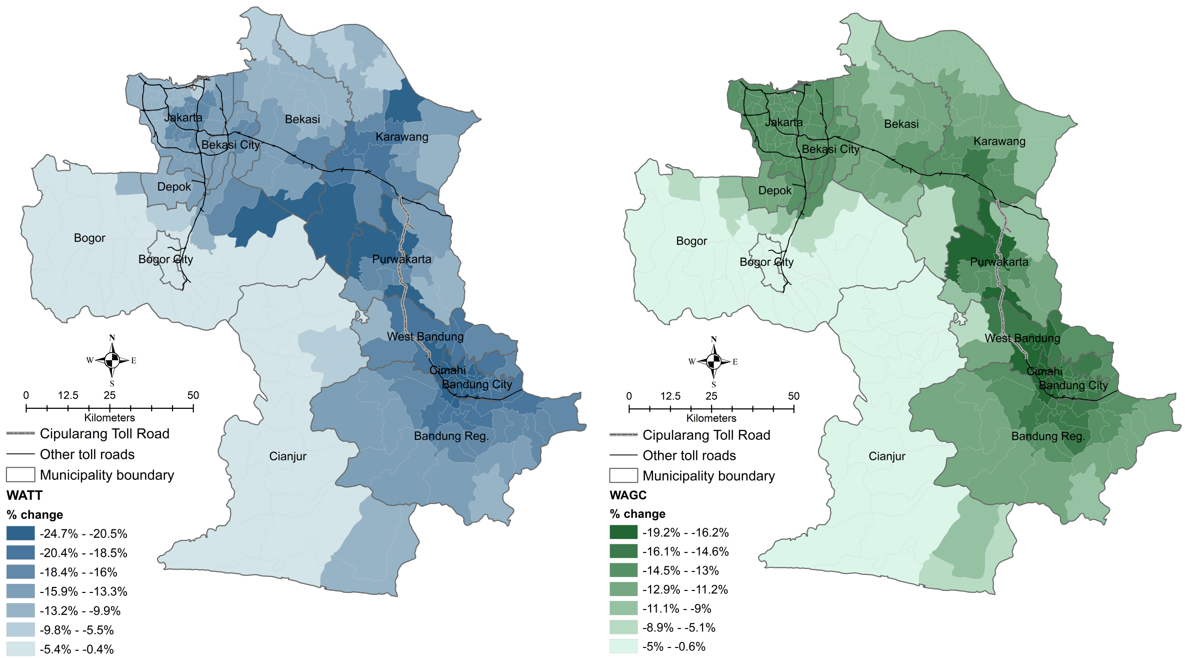


Figure 13.6: Relative difference of weighted average (left) travel time and (right) generalised cost between districts

Moreover, the potential access measures particularly highlight differences in job access between large urban agglomerations and rural areas.

Furthermore, the Shen index (Figure 13.7a) shows the proportion between the potential number of jobs that can be accessed and the potential demand for jobs. Several districts in Jakarta and Purwakarta have Shen indices equal to one, which indicates that the number of jobs and the size of the working population are in balance. A district in Bekasi, known as the largest industrial area in Indonesia, has a Shen index of more than 2.0, which signifies that there are more jobs available than workers. However, in contrast with other measures, the Shen index is lower in the scenario with the Cipularang toll road (see Figure 13.7a). The reason is that the Cipularang toll road not only increased job access, but also working population access. The Shen index decreases the strongest in the job-poor area between Jakarta and Bandung. The construction of the Cipularang toll road also enabled the working population in the two large cities to access new jobs emerging in the new industrial areas along the toll road.

Previous findings that the number of large and medium-sized industries has increased by almost 15% in Purwakarta and that the

Table 13.4: Descriptive statistics of estimated average travel time and generalised cost

Statistics	Travel Time (minutes)	Generalised Cost (1,000 IDR)
With Cipularang toll road		
mean	154.5	231.7
max	332.6	453.8
min	109.4	180.3
st. dev.	36.5	43.6
Without Cipularang toll road		
mean	167.5	233.4
max	335.1	454.3
min	129	180.6
st. dev.	35.5	43.6

industrial relocation was due to the proximity to Jakarta and the availability of cheaper labour strengthen this result.[37] The growth of new settlement areas was also observed in Purwakarta. Dorodjatoen found that people from Bandung and Jakarta were the predominant residents of the new settlements. The construction of the Cipularang toll road enabled them to obtain less expensive housing in Purwakarta and commute daily to one of the two big cities.

[37] (Dorodjatoen 2009).

Spatial equity evaluation

Equity indices Table 13.6 shows the results for both equity indices with the Shen index and with potential job access using generalised cost decay; both are weighted by the working population. access measures with time decay were not included in the equity analysis as it only took the travel time into account. This led to an overestimation

Table 13.5: Results of access measures

Weighted access measure	**Scenario**	**Impedance: Time**	**Impedance: Generalised cost**
Working population access	w/ toll road	8,135,674	11,304,273
	Without toll road	7,804,450	11,264,201
	Relative change	4.2%	0.4%
Shen Index	w/ toll road	0.73	0.73
	Without toll road	0.78	0.74
	Relative change	-5.6%	-0.41%
Potential job access	w/ toll road	6,016,274	8,251,967
	Without toll road	5,755,050	8,221,007

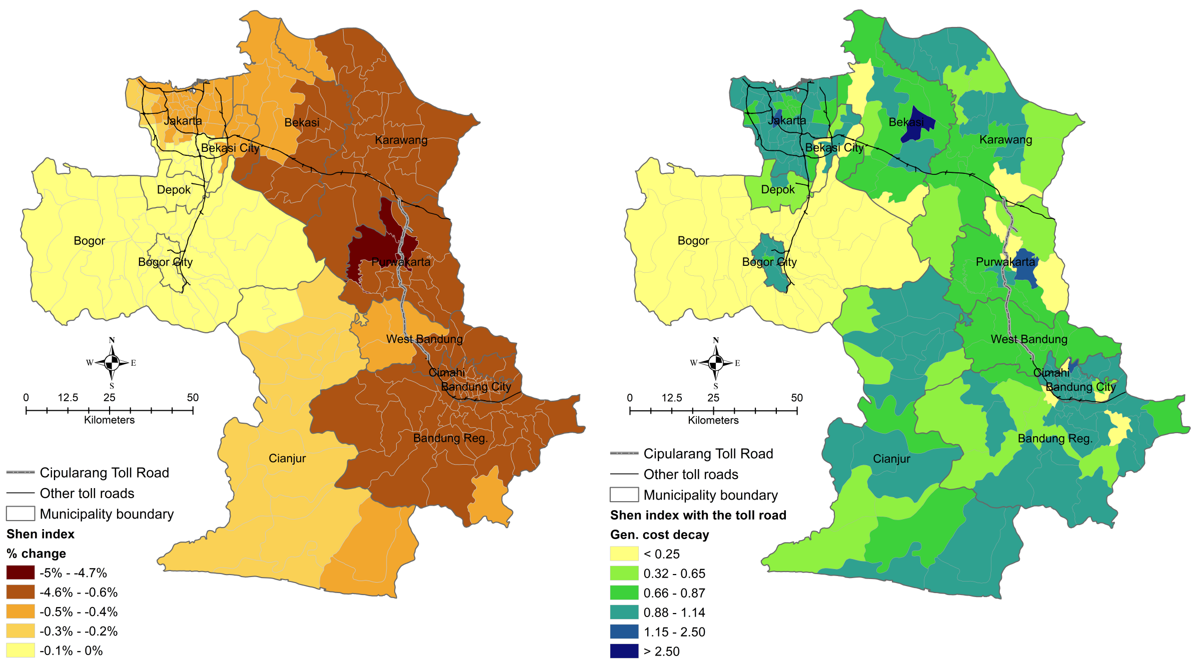


Figure 13.7: Relative changes in Shen Index with and without the toll road (left) and Shen Index with the toll road (right)

of the access impact of the toll road and, therefore, was not a good approach to measure the inequity.

In general, we found that the construction of the toll road had no impact on the average level of spatial equity as shown by the values of the Palma ratio and Gini coefficient with regard to potential job access, and of the Palma Ratio using the Shen index. However, we observed a slight increment of the Gini coefficient using the Shen index. This indicates that, overall, the introduction of the toll road has benefited high-to-medium income workers more than low-income workers, but the Palma ratio shows that people in the top 10% of incomes did not benefit more from the toll road than those in the lowest 40%.

However, this result is not fully representative, as mode choice was not taken into account. In Indonesia, low-income workers rely on motorcycles,[38] but motorcycles are not allowed on most toll roads. In practice, this means that higher-income workers benefit more than lower-income workers.[39]

Cluster analysis The Gini index and Palma ratio (see the previous section) do not explain the spatial distribution of the changes in equity and the characteristics of districts that are most likely to

[38] (Herwangi et al. 2015).

[39] See Andani et al. (2021) for a more elaborate discussion on how the travel behaviour of various population segments is affected by the Cipularang toll road.

Table 13.6: Equity indices weighted by working population, with generalised cost decay

Access measures.	Scenario	Palma ratio	Gini coefficient
Shen index	w/ toll road	1.10	0.30
	w/out toll road	1.10	0.29
Potential job access	w/ toll road	1.14	0.38
	w/out toll road	1.14	0.38

benefit from the new toll road. This section, therefore, presents the results of an analysis of the spatial distribution of access carried out with a two-step cluster method.

As all types of potential access (labour market, job and Shen index) are highly correlated (>0.9), only the Shen index with generalised cost decay is included in the cluster analysis. We consider this access measure the most comprehensive of the measures tested in this chapter since it incorporates the competition effect and is calculated using generalised cost decay. Furthermore, we also took into account residential land use growth, monthly expenditure, number of jobs and working population of the areas in the analysis.

Figure 13.8 and show the cluster map and the profiles of each cluster containing the mean of each variable (cluster centre), respectively. We obtained three final clusters (based on minimum BIC value), which we distinguished these clusters as (1) affected areas, (2) unaffected and more urbanised districts and (3) unaffected and less urbanised districts.

Cluster 1 accounts for 2.6% of the 229 districts in the area. This cluster has the lowest relative change in the Shen index (-2%), while the changes in the other clusters are almost zero, thus this cluster experienced increased inequity. This can also be seen in the mismatch between the number of jobs and the size of the working population. This cluster can also be characterized as highly accessible, as it is situated close to the toll gates and has the highest reduction of average travel time relative to the situation before the construction of the Cipularang toll road (see Figure 13.6), with the highest expenditure per capita as well. This result also in line with the result of the Shen index, as shown in Figure 13.7(left). It is consistent with the findings of several studies that the most affected areas by the construction of new motorways were areas along the roads and close to the exits.[40]

[40] e.g., (Ghani et al. 2016, Ji et al. 2014).

Variables	Cluster Centre			
	Cluster 1 Affected districts	Cluster 2 Unaffected and more urbanised	Cluster 3 Unaffected and less urbanised	Combined
Shen-index relative change	-2.02%	-0.34%	-0.48%	-0.49%
Monthly expenditure/capita (1,000 IDR)	8626	2473	1342	1750
Residential land use growth (2004-2013)	5.0%	5.2%	2.9%	3.4%
Working population	104,303	155,695	54,766	75,456
Number of jobs	14,526	138,027	36,204	55,201

Table 13.7: Final cluster centre

The shares of the number of jobs and the size of the working population in the other two clusters are somewhat proportional. However, Cluster 2 (unaffected and more urbanised districts) can be characterized as more urbanised due to its large number of workers and jobs, as well as its high rate of residential land use growth. This cluster accounts for 19.2% of the total districts in the region. Furthermore, Cluster 3 (unaffected and less urbanized districts) contains most districts in the study area (78%). This cluster is characterised by the lowest number of jobs and the smallest working population, the lowest average monthly expenditure, and the lowest residential land use growth.

These results highlight that the construction of a new toll road can have significant spatial equity impacts on areas close to the toll gates. The decreased travel times and the emergence of new employment along the toll road corridor increases the number of workers who can access employment. This cluster result explains the results of both equity indices (Palma ratio and Gini coefficient).

Conclusions

We examined the impact of the Cipularang toll road in Indonesia on job access and spatial equity by isolating the effect of the toll road. We applied a macroscopic traffic simulation model to obtain valid estimates of travel time and generalised cost. Job competition, represented by the Shen index, was also measured to reflect the distributions of employment and working population. We then assessed the equity impact by using the Palma ratio, Gini coefficient and spatial distribution of the access changes with a two-step cluster analysis.

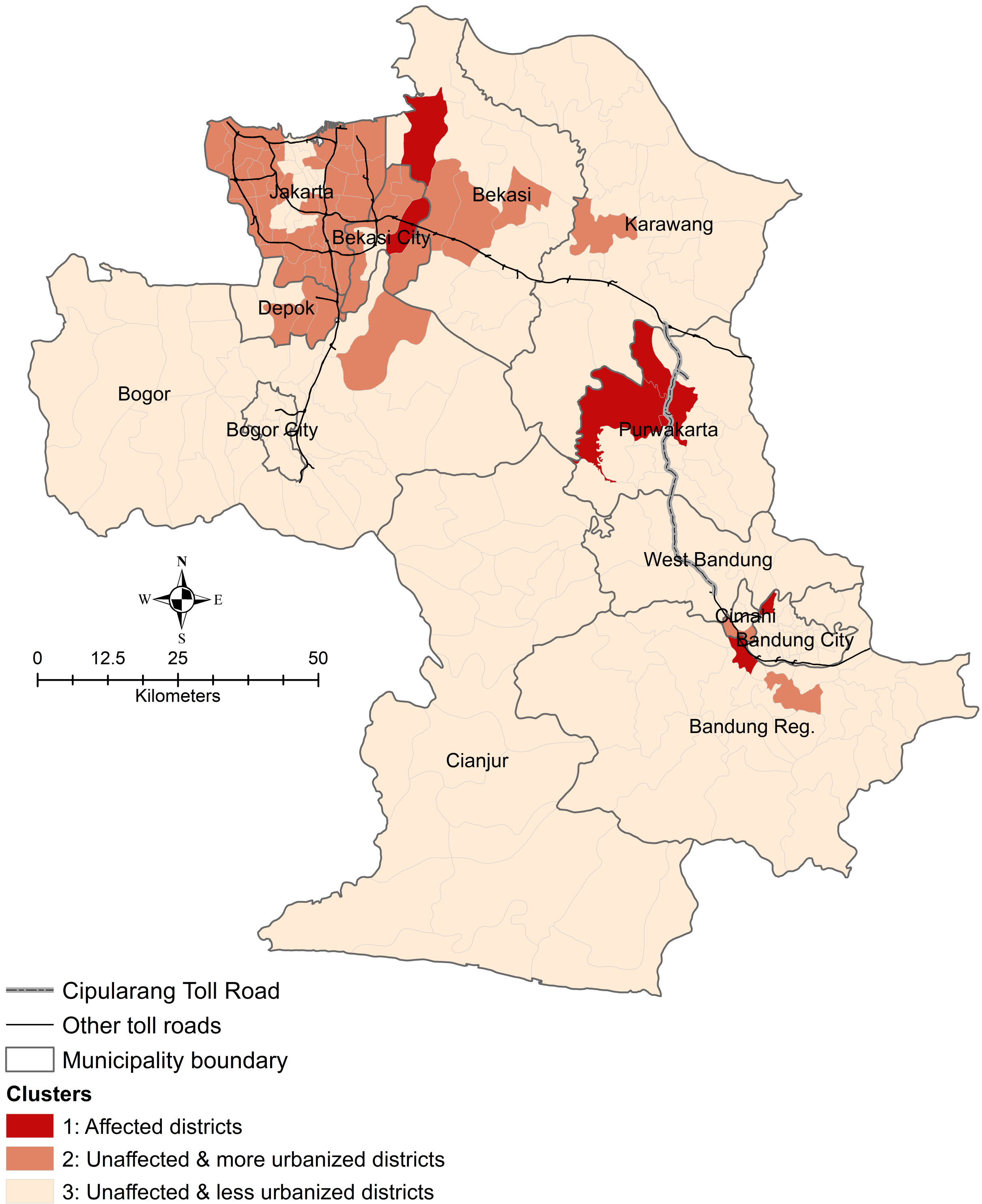


Figure 13.8: Cluster map

We found that area along the toll road and close to the toll gates are the most affected by the construction of the Cipularang toll road. Our analysis shows that the construction of the Cipularang toll road has reduced the average travel time in the Jakarta-Bandung area by 13%. For specific origin-destination pairs, the travel time is now up to 1.5 times shorter. The access analysis shows that the choice of indicator affects the results. Employment and working population access have increased by 5%. However, the toll road also increases job competition as more workers can access jobs available in the job-poor area in between Jakarta and Bandung, resulting in a small decrease in the number of accessible jobs per worker. Most affected areas have a relatively large working population compared to the number of jobs and experienced residential land use growth. We can conclude that a new toll road in developing countries with un-mature road networks can have positive as well as negative impacts on the areas close to it.

This chapter adds to the literature by examining job access and spatial equity impacts of a major toll road in a developing country context with the addition of congestion effects and stated choice-based value of time in the traffic simulation. The findings of this chapter highlight the potential value added of access analysis in the transport planning practice. access analysis can help to improve the integration of land use and transport planning with the goal of enabling all individuals, regardless of their social class or ability, to participate in desired activities in the area using the transport system.

Next

There remain opportunities to extend this research.

Firstly, we did not examine the impact of the toll road on spatial developments, e.g., distribution of employment, population or housing costs. The inclusion of these data in the measurement certainly will affect the potential job access measure.

Secondly, we were not able to estimate job access for different worker groups as reliable sector-level employment data or detailed data on the working population is not available at a high spatial resolution in Indonesia.

Finally, this chapter did not consider the complexity and differences in individual travel behaviour. It is important to incorporate the availability of transport modes at the individual level, as in Indonesia, low-income workers rely on motorcycles,

which are not allowed on most toll roads. Therefore, higher-income workers may benefit more than lower-income workers.

14
Access and Transit System Performance

Alireza Ermagun and David Levinson

Abstract: This chapter disentangles the impact of financial and physical dimensions of transit service operators on net transit access for 46 of the 50 largest metropolitan areas in the United States. We test three hypotheses: (1) financial and physical characteristics of transit systems are highly correlated with access, (2) the financial and physical characteristics exhibit constant, increasing, or decreasing access returns, and (3) the efficiency of bus systems in providing access differs from train systems with the same input. The results indicate: (1) vehicle revenue kilometres (VRK), operating expenses, frequency of the service, number of vehicles operated in annual maximum service, and number of transit employees are positively correlated with access at the metropolitan area level, (2) although VRK and operating expenses have constant access returns, frequency of the service, number of vehicles operated in annual maximum service, and number of employees display increasing access returns, and (3) using the same operating expenses for both bus and train services, the bus system provides roughly 6 times more access than train system. The bus system also operates 4 times more efficiently than the train system in providing access with the same frequency.

Introduction

Keywords: Access; National Transit Database; Public transport; Access returns; Efficiency

For decades, system profitability was a standard gauge to examine the performance of public transport.[1] Following the growth in government subsidies and public ownership of public transport systems, alternative indicators were introduced to evaluate system

[1] (Karlaftis and McCarthy 1997).

efficiency, effectiveness, and performance. The developed indicators stand on the foundation of output maximisation, including vehicle revenue kilometres (VRK) and passenger revenue. Policymakers have been interested in the scale economies of transit systems, which affects appropriates prices and subsidies. Transit system operators also desire to evaluate the consequences of potential new services or discontinuing existing ones.

A long-standing literature investigates scale economies in urban transit systems. Despite the importance of economic return to scale, the association between public transport costs and outputs of the system is inconsistent. This disparity might come from analytical and empirical sources. Pertaining to the analytical methods, studies have applied linear, log-linear, Cobb-Douglas, translog, and quadratic production functional forms to explore the scale economies of public transport systems. Each analytical method has its pros and cons. Linear models are unable to capture the economies of scale and substitution elasticities. Although the log-linear and Cobb-Douglas models allow measuring the economies of scale, they are incapable of accommodating substitution elasticities akin to linear models.[2]

[2] (Cobb and Douglas 1928).

These limitations were obviated by the introduction of the the translog function,[3] which has become widely used in understanding scale economies in public transport. A point worthy of emphasis is that the translog function model is usually criticised for a number of drawbacks. First, the cost structure of transit systems is estimated around mean production level. Second, the translog model is built on the duality theory that says a firm chooses the combination of inputs that minimises the cost of output.[4] In contrast with profit-seeking firms, allocated subsidies to publicly owned transit agencies affect the motivation to select prices and minimise costs. This shortcoming is true if the translog function is treated as an exact functional form. However, if it is used as a flexible functional form, which may be interpreted as a second-order Taylor-series approximation, there is not an issue. Finally, since the number of parameters escalate quadratically in the flexible form of the translog function, accommodating many variables in a model faces heterogeneity and multicollinearity problems.[5] In response, studies developed the quadratic ∪- or ∩-shape functional form, which allows exploration of both increasing and decreasing returns to scale simultaneously. A study of the scale economies of 3,329 US transit agencies found that the quadratic functional form performs

[3] (Berndt and Christensen 1973).

[4] (Obeng 1985).

[5] (Viton 1981).

significantly better than the linear and logarithmic functional forms, and applying the latter forms may under- or over-estimate the performance of the transit agencies.[6]

[6] (Iseki 2008).

Much of the previous studies have assessed the efficiency of transit systems by minimising costs with respect to inputs, while vehicle revenue km (miles) or passenger km (miles) is considered as the output of the system. The current study is the first to introduce transit access as the output and assess the impacts of financial and physical dimensions of transit system operators on access to jobs by transit.

Questions

This chapter investigates the associations of access to jobs by transit with financial and physical dimensions of transit system operators in 46 of the 50 largest metropolitan areas by population in the United States. The contribution is threefold. First, much of the previous research has looked at access as an input when assessing the performance of public transport systems. Little is known about the role of access as an output of transit systems. The present study introduces access as an output, which is explained by financial and physical dimensions of transit systems. Second, we are of the opinion that assuming a linear relationship between access and financial and physical dimensions of transit system is naïve. We therefore test a quadratic form of financial and physical characteristics to explore the realistic relationship between these characteristics and access. Under the umbrella of our modeling approach, we introduce the concept of "access returns." Third, although previous studies have compared the performance of bus and train systems, the knowledge about their relative performance in contributing to access is nascent. We juxtapose the efficiency of bus systems with train systems in providing access with the same input. In particular, this chapter addresses the following questions:

- How are financial and physical characteristics of transit system related to access?
- How does access change with a change in financial and physical characteristics of transit system?
- Which public transport systems are more efficient in providing access with the same service input?

Methods

Data

The core data used for the analysis were extracted from two metropolitan-level data sets. The first is access to jobs by transit calculated by the cumulative opportunities measure.[7] The data were prepared by the Accessibility Observatory at the University of Minnesota in 2014 for 46 of the 50 largest metropolitan areas in the US. Access could not be computed for 4 of the top 50 metropolitan areas due to lack of publicly published electronic schedules. The second is financial and physical characteristics of transit systems including annual VRK, operational expenses, and length route of services. We extracted this data from the publicly available US National Transit Database (NTD) for agencies serving those metropolitan areas.

[7] See chapter 1 in this volume.

A criticism of cumulative opportunities is that any threshold is arbitrary. However, the number of jobs reachable within 30 minutes is highly correlated with the number of jobs reachable in 15 or 45 minutes, and 30 minutes is just a bit larger than the average commute duration in the US. Using different thresholds, or a weighted combination of thresholds, is unlikely to make a substantive difference to the conclusions.

Since the focus of this chapter is to evaluate transit systems, the number of reachable jobs by transit, net of the number that could be reached by transit alone, is considered for analyses. We call this measured access "net transit" ($A_{nettransit,m}$) and compute it for each metro area (m). For ease of reference during this chapter, all subsequent references to "access" assume this definition. Net transit access is the difference in jobs that can be reached in 30 minutes by transit with walk access (and by walking directly if that is faster), minus the number that can be reached by walking alone, without benefit of transit (as shown in Equation 14.1). A person-weighted version of this is produced to obtain a metropolitan average (Equation 14.2).

Table 14.1 summarises number of jobs reachable by transit and walk in 30 minutes for 46 of the 50 largest metropolitan areas in the US.

Table 14.1: Number of jobs reachable by transit and walk in 30 minutes

Metropolitan Area	Population Density (Population/Km^2)	Transit Access	Walk Access
Atlanta	659	6,995	3,102
Austin	1,006	7,001	5,916
Baltimore	1,187	14,633	6,850
Birmingham	546	2,828	1,969
Boston	862	49,237	9,988
Buffalo	951	10,432	5,167
Charlotte	651	6,541	2,937
Chicago	1,361	48,116	13,965
Cincinnati	796	5,792	3,290
Cleveland	472	8,372	3,961
Columbus	778	9,506	4,280
Dallas	1,112	10,113	5,118
Denver	1,372	20,467	8,191
Detroit	1,078	6,373	3,824
Hartford	692	9,768	4,944
Houston	1,150	15,166	6,008
Indianapolis	814	6,263	3,431
Kansas City	866	6,696	3,742
Las Vegas	1,747	8,162	4,721
Los Angeles	2,703	43,430	14,490
Louisville	788	6,509	3,236
Miami	1,715	15,333	6,872
Milwaukee	974	19,216	7,444
Minneapolis	1,002	17,651	6,063
Nashville	664	5,232	2,989
New Orleans	1,382	8,364	5,274
New York	2,054	210,186	47,338
Orlando	976	4,921	3,030
Philadelphia	1,060	35,217	9,929
Phoenix	1,222	9,981	4,725
Pittsburgh	740	12,268	4,048
Portland	1,362	18,723	7,137
Providence	844	8,252	5,831
Raleigh	659	6,372	4,300
Riverside	1,369	4,346	2,613
Sacramento	1,413	11,052	5,687
Salt Lake City	1,419	13,733	6,242
San Antonio	1,137	9,849	4,087
San Diego	1,559	12,752	6,202
San Francisco	2,420	65,246	23,428
San Jose	2,247	16,441	8,476
Seattle	1,169	26,141	11,028
St. Louis	899	7,804	3,784
Tampa	985	6,865	3,705
Virginia Beach	1,078	4,784	3,165
Washington	1,340	47,759	12,310

$$A_{nettransit,m} = A_{transit,m} - A_{walk,m} \tag{14.1}$$

$$A_{nettransit,metro} = \frac{\sum_m A_{nettransit,m} \cdot Pop_m}{\sum_m Pop_m} \tag{14.2}$$

National Transit Database

To extract the financial and physical characteristics of transit systems, the transit agencies associated with each metropolitan area are extracted from the 2013 NTD. We aggregated the financial and operating variables at the Core Based Statistical Area (CBSA). This approach helped merge the NTD with the access data. Among 85 agencies, 29 of them operate in more than one CBSA. For instance, Orange County Transportation Authority operates in Los Angeles, Riverside, and San Diego. For agencies serving multiple areas, the data was allocated by the research team into the appropriate area based on the spatial distribution of service provision in each CBSA. Both the map of the transit system and Core Based Statistical Area are matched; then, the length of the transit service links in each CBSA is measured. Finally, in accordance with the extracted shares, the financial and operating expenses are allocated to each metropolitan area according to the share of service in each metropolitan area. For example, the Massachusetts Port Authority officially operates in both the Boston and Providence CBSAs. However, exploring the length of the transit system in each area shows that approximately 100% of the transit share belongs to the Boston metropolitan area.

Table 14.2 outlines the description of explanatory variables along with some statistical information regarding metropolitan areas.

Variable	*Definition*	*Average*	*St. Dev.*
E	The expenses associated with the operation of the transit agency (1,000 $US)	361,746	906,907
E_{Bus}	E only for bus services	225,499	418,646
E_{Train}	E only for train services	140,813	499,213
R	Thousand kilometres that vehicles are scheduled to or actually travel while in revenue service	54,563	118,126
R_{Bus}	R only for bus services	30,584	38,814
R_{Train}	R only for train services	24,159	83,055.4
L_{Bus}	Kilometres in each direction over which bus vehicles travel while in revenue service	3,283.5	3,030.4
L_{Train}	Kilometres in each direction over which train vehicles travel while in revenue service	317.2	538.0
Q	$= R \div (L_{Bus} + L_{Train})$	51.3	56.5
Q_{Bus}	$= R_{Bus} \div L_{Bus}$	9.0	3.6
Q_{Train}	$= R_{Train} \div L_{Train}$	42.3	55.2
V	Number of vehicles operated in annual maximum service	1,354	2,595
Y	Transit agency employees	5,220	1,1953
P	Metropolitan areas population (Thousand)	3,019	3,165
$Pop.\ Dens$	Population density on metropolitan areas (Population/km^2)	1,170	472
A_{30}	Net transit access to jobs in 30 minutes threshold	1,2063	2,4734

Table 14.2: Description of explanatory variables used in the analysis

Findings

Access returns

We explore the relationship between access and both financial and physical characteristics of transit systems at the metropolitan area level. We do not simply assume a linear relationship between access and characteristics of transit systems, rather we test the quadratic form of financial and physical factors to explore a more realistic relationship between these factors and access.

Under the umbrella of our modeling approach, we introduce the concept of "access returns." Access returns assumes the size of transit service providers affects their ability to produce access to jobs efficiently. The proposed models consider access as the output of the system. This approach helps capture more realistic changes in access resulting from variations in financial and physical characteristics at the metropolitan area level.

Access returns describes the interrelation between the amount of access to jobs provided by a transit service and the inputs of the system. In its basic usage, the access returns concept represents three distinct forms:

- **Constant returns**: Access changes proportional to the change in transit system characteristics (i.e., the changes are linear).
- **Increasing returns**: Access changes by more than the change in transit system characteristics.
- **Decreasing returns**: Access changes by less than the change in transit system characteristics.

To measure the access returns, the quadratic form of transit system characteristics is tested in the regression models. The ∪- or ∩-shape of quadratic function enables measuring the change of access resulting from changes in transit system characteristics.

The access returns is then interpreted as follows: if there is a statistically significant quadratic correlation between the access and a transit system character, the access exhibits either increasing or decreasing returns in response to the interest transit system character. It is increasing if the correlation forms the right side of the upward turned parabola or the right side of the downward turned parabola. It is decreasing if the correlation forms the left side of the upward turned parabola or the left side of the

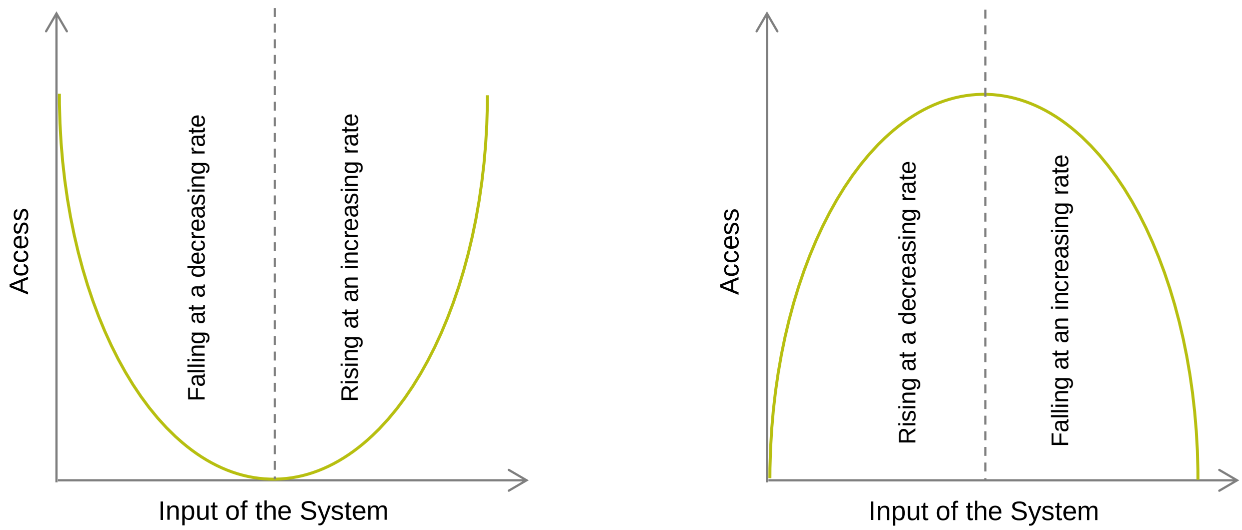


Figure 14.1: Increasing and decreasing access returns

downward turned parabola. These definitions are depicted in Figure 14.1 for ease of interpretation. There is a constant return, if the quadratic correlation between the access and the interest transit system character is statistically insignificant. With constant returns, the relationship between the transit system character and access is assumed to be linear. This linear relationship is either positive or negative depending on the sign of coefficients.

Transit system correlates of access

To measure access returns and explore the realistic correlation between access and financial and physical characteristics of transit systems outlined in Table 14.2, we postulate three major hypotheses:

- $H1$: Financial and physical characteristics of transit systems including VRK, operating expenses, frequency of service, number of vehicles operated in annual maximum service, and number of transit agency employees are highly and positively correlated with access. The magnitude of correlation, however, varies, depending on the input.

- $H2_{null}$ **(**$H2_{increasing}$, $H2_{decreasing}$**)**: The financial and physical characteristics exhibit constant (increasing, decreasing) access returns.

- $H3_{null}$ **(**$H3_{A_{bus}>A_{rail}}$**,** $H3_{A_{bus}<A_{rail}}$**):** The efficiency of bus systems in providing access is the same is (is higher than, lower than) train systems with the same input.

To test these hypotheses, we run a set of regression models. The major challenge we face in modeling is that the characteristics of the transit systems are highly correlated, and thereby developing a model using all significant variables requires caution. Neglecting to mention policy sensitive variables also spawns misspecification in policy analysis. We therefore measure access returns while embedding one transit system characteristic in each model and controlling for population density. The results of modeling are depicted in Table 14.3. Other possible transformations in linear regression such as semi-log and double-log were investigated, with simple regression presenting the best structure. The Adj. R^2 measurement is used to judge the overall fit of the models. The student's t-statistic is used to check the level of significance in hypothesis testing.

We found a positive linear correlation between VRK and access. This indicates the revenue kilometres variable has a constant access return. A similar relationship is found between the operational expenses of transit systems and access. We did not find population density significant in either of the models.

The frequency of transit service varies, and the number of jobs that can be reached at a given time varies with the headway of services. Our measure of access is averaged over time as access varies by time of day. We postulate that more frequent transit service provides more access. To test this hypothesis, the VRK is divided by directional route kilometres to obtain an indicator of transit frequency at the metropolitan area level. Looking at both the Q and $(Q)^2$ variable in Table 14.3, we find that the coefficients of both variables are significant. The coefficient of $(Q)^2$ is positive indicating the parabola opens upward and the frequency of transit service has an increasing access returns effect. Access changes by a larger proportion than the change in the frequency of transit systems.

As expected, both the number of vehicles operated in annual maximum service and the number of employees variables have a positive impact on access when we control for population density at the metropolitan area level. The quadratic form of the variables has

a positive significant coefficient indicating the parabola opens upward and both variables have increasing access returns effect.

Model	Variables	Coefficient	t-test	p-value	Adj. R^2	Access Returns	Elasticity
1	R	0.16	6.63	0.000	0.96	Constant	0.77
	$(R)^2$	5.63×10^{-8}	1.43	0.159			
	Pop. Dens	2.51	1.29	0.205			
	Constant	-563.87	-0.27	0.787			
2	E	0.02	7.58	0.000	0.96	Constant	0.66
	$(E)^2$	2.31×10^{-10}	0.44	0.665			
	Pop. Dens	2.65	1.41	0.165			
	Constant	-248.45	-0.12	0.903			
3	Q	-291.47	-1.28	0.228	0.61	Increasing	1.23
	$(Q)^2$	2.49	4.47	0.000			
	Pop. Dens	11.86	2.21	0.032			
	Constant	-1266.45	-0.19	0.853			
4	V	3.83	3.31	0.002	0.94	Increasing	0.78
	$(V)^2$	3.20×10^{-4}	4.56	0.000			
	Pop. Dens	6.50	2.89	0.006			
	Constant	-3460.24	-1.38	0.175			
5	Y	1.18	4.5	0.000	0.94	Increasing	0.71
	$(Y)^2$	9.60×10^{-6}	2.83	0.007			
	Pop. Dens	7.25	3.46	0.001			
	Constant	-4240.31	-1.75	0.088			
6	R_{Bus}	0.23	2.2	0.034	0.96	Constant	0.90
	$(R_{Bus})^2$	-1.07×10^{-6}	-1.39	0.173			
	R_{Train}	0.19	3.38	0.002		Constant	0.23
	$(R_{Train})^2$	1.69×10^{-7}	1.36	0.181			
	Pop. Dens	3.40	1.57	0.124			
	Constant	-2492.60	-1.09	0.284			
7	E_{Bus}	0.03	1.86	0.070	0.96	Constant	0.76
	$(E_{Bus})^2$	-6.56×10^{-9}	-0.29	0.771			
	E_{Train}	0.02	1.75	0.100		Constant	0.13
	$(E_{Train})^2$	4.87×10^{-9}	0.39	0.697			
	Pop. Dens	2.04	0.85	0.400			
	Constant	-93.50	-0.03	0.972			
8	Q_{Bus}	-3034.34	-1.26	0.213	0.60	Increasing	4.45
	$(Q_{Bus})^2$	205.09	1.73	0.100			
	Q_{Bus}	-183.86	-1.44	0.159		Increasing	1.01
	$(Q_{Train})^2$	2.11	3.31	0.002			
	Pop. Dens	12.49	2.28	0.028			
	Constant	3105.44	0.28	0.783			

Table 14.3: Quadratic regression model. Dependent variable: A_{30}

To give the reader a sense of quantitative impact of financial and physical characteristics of transit systems on access, we calculate the elasticity of independent variables through sample enumeration. The elasticity estimates are depicted in Table 14.3. An elasticity value shows the percentage change in the dependent variable as a result of a 1% increase in the independent variable at the margins. Two

methods are typically used for elasticity calculation: the arc elasticity method and the point elasticity method. We use the arc elasticity method, which measures the elasticity at the average. Elasticities are meaningful for small changes around the average as they are estimated for marginal changes.

A 1% increase in VRK increases access by about 0.77%. The operational expenses have less of an impact on access. A 1% increase in operational expenses is followed by 0.66% increase in access. Looking at Table 14.3, it is inferred that a 1% increase in the frequency of transit systems increases access by 1.23%. The results of the elasticity calculation indicate a 1% increase in the number of vehicles operated in annual maximum service and employees increases access by 0.78% and 0.71%, respectively.

Bus or train?

Transit systems considered for the analysis in this chapter encompass both bus and train services. Transport economists often argue that considering capital and operating costs, bus transit is more cost effective per rider than rail in most of the US. We hence evaluate the efficiency of both systems in terms of providing access to jobs by detaching the annual VRK and operating expenses of bus from train services. Table 14.3 summarizes the results of modeling.

In Model 5, the quadratic form of the annual VRK variable is not significant, while the linear form of this variable is significant for both bus and train services. This reveals annual VRK has constant access returns for both services. The similar trend is observed in Model 6, where operating expenses variable is tested as an input of the public transit system. Looking at Model 7 in Table 14.3, it is found that the quadratic form of the frequency variable is significant and the linear form is insignificant for both bus and train services. This indicates that the frequency of services has increasing access returns unlike the annual VRK and operating expenses. Comparing the access returns of bus and train services, it is then found that the form of access returns is similar between both services. Although VRK and operating expenses have constant access returns for both services, there is increasing access returns when frequency is considered as an input of the system.

When comparing the elasticity of variables in each model, however, we note that the magnitude of impacts on access is different between both services. While a 1% increase in VRK of

train service increases access by 0.23%, this increase equals 0.90% for bus services. This difference is more significant when comparing the effect of operational expenses. Access increases by 0.76% when the operating expenses of a bus system increases 1%, while this gain is only 0.13% for train systems. This reveals that by using the same operating expenses for both bus and train services, the bus system provides roughly 6 times more access than train system. Such findings can give policymakers and planners considering investments information about the possible returns. As expected, frequency of the system has one of the highest impacts on access. The results of the elasticity analyses show that a 1.01% increase in access follows a 1% increase in frequency of train system. The bus system, however, operates 4 times more efficiently than the train system in providing access with the same input.

Figure 14.2 represents the observed access amount against the predicted amount using the results of Model 5. Most of the units lie close to or at 45 degrees from the origin. Metropolitan areas on the upper left of the line have more access than predicted, while those on the lower right are underperforming. To understand the performance behavior of the model, we used 3-step post validation.[8] We do not find any significant relationship between the residuals of the model and variables used in the analysis, except the access. The results show a positive correlation between the residuals of the model and the magnitude of access. This pinpoints that the performance of the model is lower for metropolitan areas with a higher amount of access.

[8] (Ermagun 2017).

Conclusions

Boosting access to jobs is an opportunity to improve public transport ridership. Upgrading transit access requires long-term policies and investments, and is not achieved overnight. However, there are a number of strategies to improve access that agencies are capable of using to better deploy existing resources. This chapter examined the impacts of financial and physical characteristics of transit systems on access in 46 of the 50 largest metropolitan areas in the United States. We tested a set of regression models to understand how and to what extent financial and physical characteristics describe access and introduced access returns notion for the transit systems. We summarise the key findings extracted from the analysis as follows:

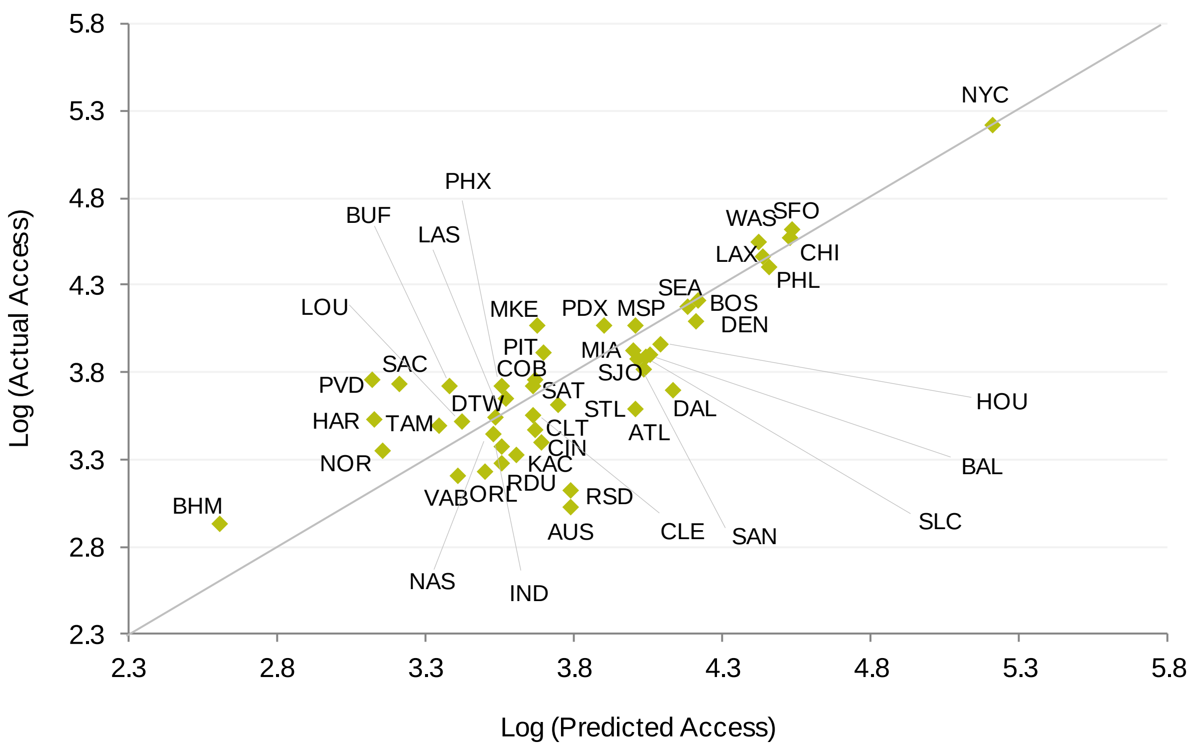


Figure 14.2: Residual plot of the quadratic Model 6

- *How do financial and physical characteristics of transit systems relate to access?* We tested how and to what extent access is described with VRK, operational expenses, frequency of the service, number of vehicles operated in annual maximum service, and transit system employees. The goodness of fit (Adj. R^2) varies between 61% and 96%, where travel VRK and operational expenses have the highest explanatory power and frequency of the service has the lowest explanatory power. Calculating the elasticity of financial and physical characteristics revealed that VRK and frequency of the service have the greatest impact on access. A 1% increase in VRK increases access by 0.77% and a 1% increase in frequency of the service increases access by 1.23%.

- *How does access change with a change in financial and physical characteristics of transit system?* Introducing and testing the access returns notion, it is found that access responds differently to variations in different financial and physical characteristics.

While VRK and operational expenses displayed constant access returns, frequency of the service, number of vehicles operated in annual maximum service, and transit system employees exhibit an increasing access returns effect.

- *Which public transport mode: bus or rail is more efficient in providing access with the same service input?* Using the same operating expenses for both bus and train services, the bus system provides roughly 6 times more access than train system. Buses also operates 4 times more efficiently than trains in providing access with the same frequency.

Next

Although we explored how and to what extent financial and physical characteristics of transit systems affect access to jobs by transit, there are still room to grow that are recommended for further exploration:

- Networks include various characteristics, including connectivity, circuity, vulnerability. and recoverability.[9] Exploring the geometric characteristics of transit networks as explanatory factors for their performance in further research, will aid in providing network design guidance.

- We discussed supply-side economies of scale by analysing the size of public transport systems rather than interoperability. The network effect (or demand-side economies of scale) in public transport systems should be studied in future research.

- The data used in the current research treat a job as a job and do not distinguish between distinct types of jobs. In particular, in measuring access to jobs, we did not consider any difference between accessing an industrial and manufacturing jobs. One research avenue is recalculating access to jobs while controlling for types of jobs. This enables examination of both scale and scope of transit systems.

[9] (Cui and Levinson 2018a;b, Ermagun and Tajik 2021).

15
Intraurban Access and Agglomeration

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Abstract: This chapter investigates the relationship between urban access and firm agglomeration, as reflected in patterns of employment densities. We use measures of access derived from the regional highway network, combined with Census block-level data on employment from the Longitudinal Employer-Household Dynamics (LEHD) to generate proxies for urbanisation and localisation agglomeration economies. These variables are employed in a set of employment density regressions for 20 two-digit NAICS code sectors to identify the propensity of each sector to agglomerate in response to varying levels of access, using the data from the Minneapolis - St. Paul, Minnesota metropolitan area for 2000 and 2010. In general, urbanisation effects tend to overshadow those of localisation effects. Moreover, these effects tend to vary by sector, with many service-based sectors showing a stronger propensity to agglomerate than manufacturing and several "basic" sectors like agriculture, mining, and utilities.

Introduction

For more than a century, urban areas have served as the loci of production for an increasing share of the economy. One important reason for this transformation has been the ability of firms to take advantage of productivity gains unique to larger urban settings. These productivity advantages stem from several sources, such as the ability to take advantage of a larger, more skilled labour pool,

Keywords: Economic development; Scale economies; Localisation; Urbanisation; Access

the spillover of knowledge among workers in a particular industry, and the shared use of certain inputs like public infrastructure.[1] These types of advantages are often described collectively under the concept of agglomeration economies.

[1] (Eberts and McMillen 1999, Overman and Puga 2010, Rosenthal and Strange 2008).

Recent advances in computation to facilitate geographic analysis, along with the greater availability of disaggregate sources of economic data, have allowed for more detailed analysis of the sources of agglomeration economies. Historically, transport networks played little role in the analysis of agglomeration economies. To the extent that transport was included, it often took the form of an infrastructure stock and was approximated by an estimate of its value, rather than the flow of services it provided. This infrastructure was assumed to take the form of a club-type good consumed by all the firms located in a given region. Accordingly, agglomeration economies were implicitly assumed to arise from urbanisation effects – the types of external scale economies that arise from access to larger, thicker markets. Other potential sources of agglomeration economies such as localisation effects, where firms are able to obtain productivity gains by locating near other firms within the same industry, were sometimes recognized but seldom directly incorporated.[2]

[2] (Rosenthal and Strange 2004).

Recent analyses of agglomeration economies have resulted from efforts to more explicitly incorporate space and the effects of transport networks into traditional production functions to measure agglomeration effects, partly motivated by theoretical developments suggesting potentially larger productivity gains from transport improvements.[3] Graham applied this approach to firm-level data from the UK, using ward-level employment data to construct a measure of urbanisation (labeled as "effective density") based on employment density discounted by distance.[4] Production functions were fitted to the firm-level data in a number of two-digit SIC (Standard Industrial Classification) industries. Results indicated that for certain industries, particularly service industries, the urbanisation effect was substantial.

[3] (Venables 2007).

[4] (Graham 2007a).

This initial framework was later extended to include a more complete measure of access to economic activity as a surrogate for urbanisation in the form of a generalised cost variable.[5] The use of generalised cost more completely captures the effect of the cost of transport by including the effects of congestion, which Graham cited as an important contributor to diminishing returns in the most highly urbanised locations. Further extensions allowed for

[5] (Graham 2007b).

decomposition of elasticity estimates to differentiate agglomeration effects from returns due to the increased efficiency of factor inputs,[6], the inclusion of measures of localisation,[7] and for a nonlinear relationship between access and productivity.[8]

[6] (Graham and Kim 2008).

[7] (Graham 2009).

[8] (Graham and Van Dender 2011).

In addition to being used as an improved proxy for urbanisation effects in production functions, measures of urban access have also been applied to estimate the productivity effects from agglomeration via wages. A panel of 50 large US metropolitan areas ("large" defined as a population greater than one million) was employed to estimate the relationship between agglomeration and real average wages.[9] Two different measures of agglomeration were compared, one using a conventional measure of employment density and the other using a formal measure of employment access to incorporate the more realistic effects of transport networks. The authors tested both a 60-minute time threshold measure of employment access as well as a series of time threshold variables designed to capture the incremental contributions of additional levels of access at greater distances, and to approximate the decaying effect of agglomeration at greater distances. Results indicated that both measures of urban size produced roughly similar estimates of agglomeration economies, with real average wages rising by between 7 and 10 percent in response to a doubling of employment density or jobs accessible within 60 minutes. Also, the travel time thresholds defined for the access variables seemed to indicate a somewhat limited spatial scope of agglomeration, with most of the effects concentrated within 20-minute travel time bands.

[9] (Melo et al. 2017).

While most of the studies relating transport to agglomeration economies and productivity more broadly tend to focus on road networks,[10] there have been some efforts to examine the relationship between alternative modes, most notably public transit, and the potential for agglomeration.[11] One important weakness is that much of the previous studies have not incorporated actual transit networks into their analysis. The real value of public transit networks in contributing to urban agglomeration economies lies in its ability to expand the reach of markets and reduce the friction of distance for firms and households within urban areas.Hence, a measure of the service provided by the network itself, in the form of access, is a more appropriate concept for capturing the ability of public transit systems to contribute to urban agglomeration.

[10] (Melo et al. 2013).

[11] (Drennan and Brecher 2012).

Overall, previous studies overwhelmingly chose metropolitan areas as the unit of analysis and overlooked agglomeration effects

within a metropolitan area. They often used productivity measures for all economic sectors (e.g., average wage and employment density) and largely ignored the varying effect of different sectors. In this chapter, we aim to examine the effects of urbanisation economies and localisation economies on employment density in different economic sectors, using data from a single region. The use of realistic roadway networks with observed travel times allows us to refine the definitions of sources of agglomeration effects in order to better match the spatial characteristics which define their extent within an urban economy. These and other methodological considerations are discussed in greater detail in this chapter.

Questions

The role transport networks play in fostering agglomeration is still the source of considerable debate. In principle, improved transport networks might enhance agglomerative forces by lowering transport costs for firms and expanding the spatial reach of markets for labour and other goods. If true, this could have implications for the types of investments in network improvements that generate greater economic development outcomes. In this chapter, we incorporate direct measures of the service provided by regional transport networks in the form of measures of access, which measure the ease of accessing various destinations, and assess their influence on the propensity for firms to agglomerate across several sectors. Variations in access are hypothesized to affect the propensity for agglomeration, as measured by employment densities.

Using data from the Minneapolis - St. Paul metropolitan area, this chapter employs negative binomial regression to examine the effects of access measures on employment densities of 20 industrial sectors. This chapter addresses the following questions:

1. Which industrial sectors are more responsive to agglomeration economy?

2. Which of urbanisation effects and localisation effects dominates the propensity for agglomeration?

Our approach differs somewhat from many prior empirical studies in that we examine intraurban variations in agglomeration across sectors, rather than using entire urban areas as sample units. We also investigate variations across economic sectors in the degree

of agglomeration. The use of disaggregate access measures allows us to distinguish between sources of agglomeration, as we develop separate, industry-specific measures to proxy for localisation effects in contrast to urbanisation effects, which are assumed to arise from greater access to all types of activity in the region.

Methods

This chapter is primarily concerned with the relationship between access and urban agglomeration at an intraurban level. As the preceding discussion noted, there is evidence of the spatial attenuation of agglomeration economies within urban areas for localisation effects and possibly also for urbanisation effects. We therefore need to be able to measure agglomeration at a relatively fine spatial resolution in order to capture these attenuation effects, to the extent that they may exist.

Research design

The variable that will be employed to measure agglomeration effects is employment density, measured as employment per square kilometer. While employment density does not directly yield productivity benefits from agglomeration, it is a useful proxy for the effects of agglomeration, since employment densities of the areas with strong agglomeration tend to be high. Densities are measured at the level of census blocks and aggregated up to transport analysis zones (TAZ) for the Twin Cities region. The use of this level of aggregation is designed to correspond with the level at which measures of urban access are available.

There are two main considerations that guide our empirical approach. The first is that there ought to be separate variables to capture urbanisation and localisation economies. As outlined previously, urbanisation economies are external to firms and their industries, and so have a wider geographic scope. For example, a 60-minute employment access measure can approximate the effects from urbanisation. In addition we include measures representing incremental travel time thresholds throughout the region.[12] We adopt this method as well in order to test for the attenuation of urbanisation effects over greater distances. Localisation economies are approximated with measures of access to own-sector employment for each of the 20 two-digit NAICS (North America

[12] Following (Melo et al. 2017).

Industry Classification System) code sectors within 10 minutes. They should be spatially fairly limited given the evidence discussed previously regarding their rather sharp attenuation.

The second consideration is that estimates of urbanisation and localisation effects ought to be allowed to vary across sectors. This implies that separate equations ought to be estimated for each of the sectors in the data set. Certain types of sectors like agriculture and mining are likely to be less susceptible to agglomeration, while others such as manufacturing and various service sectors can be expected to demonstrate higher levels of agglomeration.

Data sources and variables

LODES Data. The data regarding the number of jobs and workers came from the LEHD Origin-Destination Employment Statistics (LODES) of the US Census Bureau, in which LEHD stands for Longitudinal Employment Household Dynamics. The LODES contain three groups of information including Origin-Destination (OD) data, Residence Area Characteristic data (RAC), and Workplace Area Characteristic (WAC) data. The OD data specify the origins and destinations of commuters, which are not used in this analysis. The RAC and WAC contain the number of jobs by sectors living or working in each census block, which are used to measure access to workers and access to jobs, respectively. Since LEHD was initiated in 2002, we extracted the LODES data for the state of Minnesota in 2002 and 2010 to approximate the job and worker data in 2000 and 2010.

Speed and Network Data. Acquired by the Metropolitan Council (the Twin Cities' regional planning organization) for the Twin Cities, both road network and auto speed data for use in computing 2010 access measures came from TomTom International BV. The network is displayed as a shapefile that can be directly used in GIS software. The total number of links in the Twin Cities on the TomTom network is 48,009. The road network can be linked with the TomTom speed data. We derived the 2010 auto speed from the 2011 TomTom data, which were collected and aggregated based on millions of GPS logging and navigation devices. The TomTom speed data were organized based on road classifications, time periods and speed percentiles. First, based on the Functional Roadway Classifications (FRC), speed data were categorized into 4 groups, of which FRC0 to FRC4 were combined. For each category of FRC,

speed data were separately recorded at different times of a day including overnight (10PM-5AM), morning peak hours (5:00 AM-7:00 AM and 7:00 AM-9:00 AM), mid-day (9:00 AM-2:00 PM), evening peak hours (2:00 PM-4:00 PM and 4:00 PM-6:00 PM), and evening (6:00 PM-10:00 PM). Moreover, the TomTom speed data provided different percentiles of speed measurements. The access measurement in this chapter used the median speed of morning peak hours during 7:00 AM-9:00 AM.

Zone-to-zone travel time matrices for the year 2000 were obtained from a previous study which derived them via travel time skims from the region's travel forecasting model.[13] Travel times were measured between all the OD pairs at the level of TAZs based on the year 2000 regional highway network.

[13] (Levinson et al. 2010).

Access measures

The cumulative opportunity measure is used for access measurement.[14]

[14] See chapter 1 in this volume.

When developing models, we used an annulus access measure. It is calculated based on the difference in access between two adjacent travel time thresholds:

$$A_{i,\Delta_T} = A_{i,T} - A_{i,T-10} \tag{15.1}$$

$$A_{i,\Delta_{10}} = A_{i,10} \tag{15.2}$$

Where:

T equals 20, 30, 40, 50, and 60 minutes respectively,

$A_{i,T}$ stands for the access within the time threshold of T.

So $A_{i,\Delta_{10}}$ measures the number of opportunities with 10 minutes of travel time, $A_{i,\Delta_{20}}$ measures the number of opportunities between 10 and 20 minutes, and so on. The procedure to create access measures is described as follows:

- *Access by auto in 2010*

  For this measurement, ArcGIS was used to search the shortest travel time path between each of the OD pairs at the block level based on the TomTom speed data and the linked road network. The travel time was recorded as the C_{ij} to construct travel time matrix. The 2010 LODES data were joined with the travel time matrix. Then the access matrix is calculated based on the pre-determined time thresholds (10, 20,..., 60 minutes).

- *Access by auto in 2000*

  Since the travel time matrix by auto in 2000 was measured at the 2000 TAZ level, it was joined with the 2002 LODES data to compute the 2000 access matrix with the pre-determined time thresholds.

Moreover, all the access matrices are displayed using the 2000 TAZ system, which has 1,201 TAZs in total. Block-level measures of access were converted to TAZ-level measures using a population-weighted average of blocks within a given TAZ. The modeling is also based on the data of the 1,201 TAZs.

Modeling approach

A negative binomial regression with robust error is employed to estimate the influence of access on employment density. Previous studies often model employment density in a logarithmic function.[15] However, if the error term is heteroskedastic, the estimates from the log-linear function are biased while a Poisson-family regression with robust error is preferred.[16] Because some TAZs may not have any jobs for a particular industry, employment density of the industry in those zones is zero. To handle excessive zeros in industry-specific employment density, we adopted negative binomial regression (NBREG).

[15] (McMillen and McDonald 1997, Small and Song 1994).

[16] (Krizek et al. 2009, Owen and Levinson 2014).

With a negative binomial link function and robust error, employment density can be expressed as a function of access measures. Here, the access measures include job access by auto and worker access by auto. Each of the access measures is expressed as the following weighted cumulative opportunity, or gravity function:

$$A_w = \sum_{i=1}^{6} O_i e^{-b \times i \times 10} \tag{15.3}$$

$O_i, i = 1, ..., 6$ measures the opportunity between 0-10, 10-20, 20-30, 30-40, 40-50, 50-60 minutes of travel time by auto, respectively. The opportunity indicates the number of jobs (J) or workers (W). Here we assume that jobs and workers outside of the one-hour travel time buffer do not impact employment density. Because job access by auto and worker access by auto are highly correlated in this chapter,

with a correlation coefficient larger than 0.95, we sum the two access measures to construct a composite measure for auto access.

$$A_{w,auto} = \sum_{i=1}^{6} O_{J_i,\text{auto}} e^{-b\times i\times 10} + \sum_{i=1}^{6} O_{W_i,\text{auto}} e^{-b\times i\times 10} \qquad (15.4)$$

The choice of b is based on a grid search technique. In particular, we assume that employment density is a function of auto access and then seek the value of b that maximizes the pseudo-R^2 of NBREG for all jobs. We find that in 2010, the R^2 is maximized when b = 0.2 and in 2000, the R^2 is maximized when b = 0.25. To facilitate the comparison between 2000 and 2010, we choose b = 0.2 for further analyses.

Hypotheses

The specification of the employment density equation gives rise to a pair of hypotheses regarding the effects of the access variables on employment density at the TAZ level. Two specific hypotheses are examined here:

1. *Sectoral hypothesis*: Different economic sectors are likely to have different agglomeration responses to access. Service-related sectors are anticipated to have the strongest agglomeration effects (especially localisation), along with manufacturing. Agricultural, extractive (e.g. mining), and utilities are less likely to agglomerate. The null hypothesis is that there is no statistically significant difference across sectors; that is, the elasticities for each sector are equal to those of the aggregate economy.

2. *Cross-sectoral hypothesis*: Individual sectors rely only on own-sector access (localisation) for agglomeration. There is no contribution to agglomeration from access to other sectors (urbanisation).

Findings

In this section, we estimate models for employment density in each of the 20 sectors. Again, for urbanisation economies, we choose the access measure in which the opportunity includes jobs and workers in all sectors and the friction factor is set at 0.2. For localisation economies, we use the number of sector-specific jobs within a 10-minute driving distance. We test two versions of the localisation

economy variable. In the first version, the number of sector-specific jobs includes jobs within the observed zone, whereas in the second version, these jobs are excluded.

Table 15.1 presents the results when the number of jobs for the observed zone are excluded from the localisation economy variable's calculation. The elasticities for the urbanisation economy are similar.

In Table 15.1, the correlation coefficient between the elasticities of the urbanisation economy variables between 2000 and 2010 is 0.86, while the correlation coefficient between the elasticities of the localisation economy variables is 0.67. Therefore, the estimated urbanisation effects appear to be more robust than the localisation effects across time.

The top eight sectors with the strongest urbanisation effects in 2000 are similar to those for 2010. Real estate ranks 2$^{\text{nd}}$ in 2010 but ranks the 12$^{\text{th}}$ in 2000. The specific rankings for other sectors vary slightly between 2000 and 2010.

It is worth noting that the correlation between the urbanisation economy and localisation economy variables is fairly high. In 2010, for all but three sectors (mining, agriculture, and public administration), the correlation coefficients between the variables are larger than 0.7. This finding holds regardless of how the localisation variable is specified. While some correlation between the two variables ought to be expected, as the own-sector jobs are a subset of total employment for purposes of access calculation, the level of correlation between them casts some doubt on whether two variables are truly independent.

Returning to our earlier hypotheses about the relationship between access and sector-specific agglomeration, our first hypothesis (sectoral variation) seems to be borne out by the evidence on sector-by-sector density elasticities. Service-oriented sectors seem to show the strongest propensity for agglomeration, but the source of this agglomeration comes from urbanisation rather than localisation effects. The manufacturing sector shows modest (generally less than unity) positive agglomeration effects from both urbanisation and localisation economies, while sectors such as agriculture, mining, utilities and construction seem to show weak propensity to agglomerate.

The second hypothesis (cross-sectoral hypothesis) regarding reliance on own-sector access for agglomeration seems to find little support. Employment density in several of the sectors examined have no statistically significant relationship to our measure of

	Urbanization	2010 Rank	Localization	2010 Rank	Urbanization	2000 Rank	Localization	2000 Rank
Information	5.228	1	-1.574	20	3.304	2	-0.554	19
Real Estate and Rental and Leasing	5.034	2	-1.282	18	1.689	12	0.203	7
Management of Companies and Enterprises	4.293	3	-0.706	16	2.955	3	-0.148	12
Arts, Entertainment, and Recreation	4.289	4	-1.394	19	2.1	8	-0.078	11
Finance and Insurance	4.142	5	-0.575	13	3.636	1	-0.609	20
Professional, Scientific, and Technical Services	3.882	6	-0.605	14	2.92	4	-0.337	17
Administrative and Support and Waste Management and Remediation Services	3.747	7	-0.693	15	2.533	5	-0.172	13
Utilities	3.686	8	-0.528	12	1.857	10	0.131	10
Other Services [except Public Administration]	3.056	9	-0.71	17	2.137	7	-0.208	14
Accommodation and Food Services	2.715	10	-0.496	11	2.244	6	-0.271	16
Health Care and Social Assistance	2.103	11	0.17	7	1.722	11	0.191	8
Retail Trade	1.789	12	0.041	9	1.018	15	0.638	2
Educational Services	1.753	13	0.022	10	1.883	9	-0.238	15
Public Administration	1.562	14	0.38	5	1.087	14	0.285	5
Transportation and Warehousing	0.987	15	0.562	4	0.972	16	0.18	9
Construction	0.916	16	0.699	3	0.946	17	0.365	4
Manufacturing	0.506	17	0.798	2	0.726	18	0.576	3
Wholesale Trade	0.339	18	1.584	1	1.088	13	0.67	1
Agriculture, Forestry, Fishing and Hunting	0.083	19	0.152	8	-0.028	20	-0.355	18
Mining, Quarrying, and Oil and Gas Extraction	-0.102	20	0.199	6	0.416	19	0.219	6

Notes: The indicator of localisation economy excludes industry-specific jobs in the observed zones.

Table 15.1: Elasticities of urbanisation and localisation economy

localisation, proxied by own-sector employment access within 10 minutes. The magnitude of density elasticities with respect to total employment, our measure of urbanisation, tends to dominate the elasticities with respect to own-sector employment.

It is also worth noting that we have tried to explore the agglomeration effects of job access and worker access by transit, using the transit travel time matrix developed by the Accessibility Observatory and the Access to Destinations study by the University of Minnesota.[17] The modelling procedure is similar to the present study. We also tried to integrate auto access and transit access in the regression equations of employment densities. However, both results are hard to explain and inconclusive. Accordingly, we did not report them here.

[17] (Krizek et al. 2009, Owen and Levinson 2014).

Conclusions

Our understanding of agglomeration economies and the role of transport networks in promoting them continues to evolve. This chapter contributes to the base of knowledge by offering new empirical evidence on intraurban patterns of agglomeration based on small-scale geographic data on job density from the Twin Cities. The employment density elasticities reported here for two-digit NAICS code sectors incorporate realistic travel time estimates for road networks in order to approximate the role of transport costs in the urban economy, but also allow for distinction between urbanisation and localisation effects as sources of agglomeration.

Our findings indicate that in general urbanisation effects tend to dominate localisation effects across a range of economic sectors. This result tends to corroborate the findings of other studies which have found few or no positive agglomerative effects from localisation but significant urbanisation effects at higher levels of aggregation.[18] Also, the magnitude of our estimates of urbanisation and localisation economies seem to vary significantly across economic sectors. In general, service sector employment densities tend to be most prominently correlated with high levels of access. Sectors traditionally associated with CBD (central business district) locations like finance, insurance and real estate and other sectors such as management of companies and enterprises, information, and arts and entertainment have the largest density elasticities. In contrast, sectors such as agriculture, mining and construction tended to show a lower propensity to agglomerate.

[18] (Desmet and Fafchamps 2005, Fallah et al. 2013).

The results offer qualified support for the notion that high levels of access may be linked to gains from agglomeration. Though they are limited by the cross-sectional nature of our data, the employment density regressions suggest that certain economic sectors, primarily those involved in finance, insurance, real estate, information, and arts and entertainment, tend to place a premium on being able to locate in high-access locations. From the perspective of transport planning, these findings tentatively suggest that there is a valid rationale for pursuing projects and policies that limit the effects of congestion on the region's roadway networks. To the extent that congestion reduces the access provided by the network, it will affect the ability of firms to benefit from the types of urbanisation effects documented in this chapter, such as labour pooling and the use of shared inputs among firms in unrelated

industries. Improvements to the network that lower travel time thus can expand the scope of markets and enhance the matching process between firms and their workers, as well as customers and suppliers. Efforts on the part of planners to directly identify the sources of these benefits and incorporate them into project appraisal practices seem warranted.

Next

Some practical issues within the scope of this analysis are of interest to future research. The definition of the localisation variable may need to be refined. Our analysis settled on a 10-minute measure of own-sector employment access, but other specifications may be worth investigating. Other studies of firm localisation suggest that localisation takes place at small geographic scales, but that its degree differ greatly across industries.[19]

[19] (Duranton and Overman 2005).

Additionally, it is desirable to develop a time series of access measures using a single source of travel time data. The use of two different sources in the present study, with one representing modeled travel times and the other representing real travel time, limits the comparability of the results across years and the ability to estimate the results of incremental changes. The increasing availability of observational data from real-time sources should aid in this improvement in future studies.

This chapter uses zone-level data to investigate the relationship between access and agglomeration at an intra-urban level. While this approach allows for a reasonably small-scale level of geography which more closely approximates the firm-level nature of economic decision-making, the reliance on employment data does not allow for direct estimation of the welfare benefits of agglomeration. While employment density generally represents an outcome of agglomeration processes, it may be seen as a proxy for the effects of agglomeration on productivity. Obtaining more direct estimates of productivity effects through its effects on output levels or land rents would be a useful next step, and such results could be compared with the elasticities derived from the employment density data in the present study. Such an analysis would likely require the identification of a suitable source of firm-level microdata.

16

Transit Access Performance Across Chicago

Fatemeh Janatabadi, Nazanin Tajik, and Alireza Ermagun

Abstract: This chapter studies the spatial and temporal disparity of modal access to employments by measuring the Modal Access Gap (MAG) in Chicago and its nine neighborhoods. Access to employment is calculated for transit, auto, and walk in twelve 5-minute travel time thresholds at the Census block group level. First, a gradual reduction in MAG can be seen in Chicago and across its neighborhoods with an increase in travel-time thresholds. Second, different neighborhoods, depending on their proximity and distance from the Central Business District (CBD), display distinct MAG variations. The modal access gap, therefore, should not be measured in isolation of the spatial and temporal dimensions of the transit service. Third, assigning a single MAG score to the city at a specific travel-time threshold describes the city transit system imprecisely. Comparing transit and walk, the city MAG value inclines toward portending higher transit efficiency for its subareas. While comparing transit and auto, the city MAG suggests an inferior transit performance compared to the neighborhoods' average. This chapter informs urban planners and policymakers of the effects of travel time and space on access analysis. Inaccurate perceptions of transit performance prevent the development of an efficient and equitable transit system.

Introduction

Keywords: Transit performance; Public transit; Transit effectiveness; Urban planning; Disparity of Access

Public transit has been part of urban mobility in American cities as early as the emergence of steam ferry services, horse-drawn buses, and horse railways. Following modernization and urban

industrialization, the sovereignty of non-motorized mobility perished, enabling the electric streetcar to dominate mass transit. This did not last long. The dissolution of public transit in the face of a fierce opponent, private automobile, commenced; automobile ownership began to rise, and the public transit ridership started to decay.

Building sprawling, auto-centric cities that could not easily be served by public transport derailed efforts to extend this mode of travel. Auto-oriented development aside from annihilating transit also inflicted traffic congestion, air pollution, and social inequity on cities.[1] As a panacea for the ramification of auto-centric development, attention, once more, turned to public transit expansion. Public transit's moribund state, however, impeded any change, requiring federal financial aid and subsidy.

[1] (Ibraeva and de Sousa 2014).

The first US federal initiative in support of the public transit industry was authorized during the 1960s. Municipalities used the capital grants to improve private transit sectors, and the number of publicly owned transit associations soared. Despite the financial aids, transit remained unappealing, with its ridership continuing to fall. Allotting further financial aid required legitimate justifications.[2] This laid the groundwork of an evaluation process for measuring the efficiency and effectiveness of transport plans.[3] Transit systems were evaluated by models that focused on mobility as a goal of the system. This means how far you can go with transit in a given time. The ability to reach destinations rather than mobility *per se*, however, gradually formed the access-oriented development strategy as a form of evaluating transit systems and urban design.[4]

[2] (Hess and Lombardi 2005).

[3] (Deboosere et al. 2018, Lyu et al. 2020).

[4] (Lyu et al. 2020). Also see chapter 14.

Access is defined as the ease of reaching desired destinations and is a function of mobility and land use. As cities vary in mobility, transport infrastructure, and land use, access to desired destinations is expected to differ between cities[5]. This difference also exists within a city, by the same token. It is then not surprising to expect the Modal Access Gap (MAG) within and between cities due to transport infrastructure and land use policies and plans. Different approaches have been used to calculate the modal access gap. This includes comparing the value of access by different modes,[6] calculating the ratio of access by different modes,[7] and calculating the standardized of the difference between access by different modes.[8] The latter, known as the Modal Access Gap (MAG), was first deployed by[9] to measure the access gap between public transit

[5] (Ermagun 2021).

[6] (Kawabata and Shen 2007).

[7] (Ben-Elia and Benenson 2019, Benenson et al. 2017).

[8] (Kawabata 2009, Kwok and Yeh 2004).

[9] (Kwok and Yeh 2004).

and auto. A similar concept named Modal Access Disparity (MAD) examines the spatial variations of access gap between commuting modes.[10]

[10] (Kawabata 2009).

Existing research measures the modal access gap between transit and auto for multiple cities[11] and within the city.[12] These studies are summarized in Table 16.1. Reviewing studies measuring modal access gap, it is noticed that a significant difference exists between American and non-American cities. MAG analyses in American cities have usually shown large gaps between transit and auto, indicating auto provides better access than transit. Kawabata used cumulative employment opportunities at 30, 45, and 60 minutes of travel time thresholds to measure the MAG index in Boston and San Francisco.[13] The results indicated that both cities are completely auto-access-oriented, with MAG indices ranging from -0.85 to -0.75. Studies measuring the modal access gap in non-American cities suggested relatively lower gaps between transit and auto. For the study area of Hong Kong, the MAG index was measured in 1991 and compared with that in 1996.[14] The results showed that Hong Kong is an extremely transit-access-oriented city with MAG indices of 0.93 and 0.85 in 1991 and 1996, respectively.

[11] (Deboosere et al. 2018, Wu et al. 2021).

[12] (Kawabata and Shen 2007, Yang et al. 2017).

[13] (Kawabata 2009).

[14] (Kwok and Yeh 2004).

Overall, global research suggests that the modal access gap between auto and transit is noticeable in cities with low-density and low provision of transit services, leading to highly auto-oriented urban structures.[15] These characteristics are best described by American urban structures. Hong Kong and Tokyo, however, with high population densities and abundant transit services present lower gaps between transit and auto. In Hong Kong, for instance, access by transit was remarkably higher than auto, indicating almost complete transit-access-orientation.[16] Findings highlight the low transit efficiency in the American metropolitans compared to other cities around the globe.

[15] (Kawabata 2009).

[16] (Kwok and Yeh 2004).

Questions

Existing research (1) largely measures the access gap between transit and auto, and consequently little is known about the gap between transit and walk, (2) measures the modal access gap for a singular travel time threshold, and (3) is dominated by modal access gap measurement at the city level with a few exceptions.[17] This chapter is a natural continuation of measuring the modal access gap, and addresses the following questions:

[17] (Guan et al. 2020, Yang et al. 2017).

Table 16.1: Summary of modal access gap results in the literature

City	MAG	Source
Boston 1990	-0.83	(Kawabata 2009)
Boston 2000	-0.75	(Kawabata 2009)
San Francisco 1990	-0.85	(Kawabata 2009)
San Francisco 2000	-0.78	(Kawabata 2009)
Tel Aviv	-0.58	(Benenson et al. 2010)
Helsinki	-0.24	(Salonen and Toivonen 2013)
Hong Kong 1991	0.93	(Kwok and Yeh 2004)
Honk Kong 1996	0.85	(Kwok and Yeh 2004)
Guangzhou	-0.31	(Yang et al. 2017)
Warsaw	-0.045 to 0.151	(Niedzielski and Kucharski 2019)

- What is the modal access gap for transit, auto, and walk in the City of Chicago?
- How does the modal access gap change temporally?
- How does the modal access gap change spatially?

Analyses are conducted in the City of Chicago and its nine neighborhoods to compare the modal access gap within the City. Chicago is an appropriate candidate for two reasons. First, Chicago is ranked 3rd for access to jobs by transit and 4th for walking at the national level.[18] The results, therefore, will be a reference point for evaluating the modal access gap of American cities. Second, Chicago, ranked 3rd in the nation for residential segregation, is a diverse city in terms of physical structure, spatial pattern, location, and function of civic establishments as well as socio-economic characteristics.[19]

[18] (Ermagun and Tilahun 2020, Levinson 2013).

[19] (Talen 2010).

We measure access to jobs by three modes of transit, walk, and auto, and calculate the modal access gap for different travel times in the entire city and across its neighborhoods.

Methods

The cumulative number of jobs that can be reached by transit, walk, and auto across the City of Chicago is obtained from the Accessibility Observatory at the University of Minnesota. It, geographically, covers nine "sides" or "neighborhoods" including: Far North Side, North Side, Northwest Side, Central, West Side,

Southwest Side, South Side, Far Southwest Side, and Far Southeast Side, as portrayed in Figure 16.1. Access is calculated at the census block group geographical level using Cumulative Opportunities Measure.[20] The travel time calculation for transit incorporates walking, in-vehicle, transfer, and wait times.

[20] See chapter 1 in this volume.

To measure the access gap between transit, walk, and auto, we use the Modal Access Gap (MAG). The MAG is defined as the standardized of the difference between the access by two different travel modes.[21] Equation 16.1 represents the access gap between transit (A_T) and auto (A_A). The MAG_{TA} index ranges from -1 to 1 and indicates the extent to which the auto-access-orientation or transit-access-orientation is prevalent. If the MAG_{TA} equals -1, the area is extremely auto-access-oriented, and transit fails to provide service. If the MAG_{TA} equals 1, the area is extremely transit-access-oriented.

[21] (Kwok and Yeh 2004).

$$MAG_{TA} = \frac{A_T - A_A}{A_T + A_A} \tag{16.1}$$

Equation 16.2 represents the access gap between transit and walk (A_W). Like the MAG_{TA}, the MAG_{TW} ranges between -1 and 1. It, however, is an indication of the transit service effectiveness. If the number of jobs reached by walk is more than by transit, it is interpreted that transit failed in providing an effective service. This happens when MAG_{TW} is less than 0. In contrast, the transit effectiveness increases as MAG_{TW} gets closer to 1.

$$MAG_{TW} = \frac{A_T - A_W}{A_T + A_W} \tag{16.2}$$

The MAG, mathematically, is related to the simple ratio of two different access travel modes. Table 16.2 summarizes the relationship for eight categories of the MAG index. The access ratio represents the number of jobs reached by transit divided by the number of jobs reached by walk or auto. This conversion chart gives the reader a better understanding of the access gap between two travel modes.

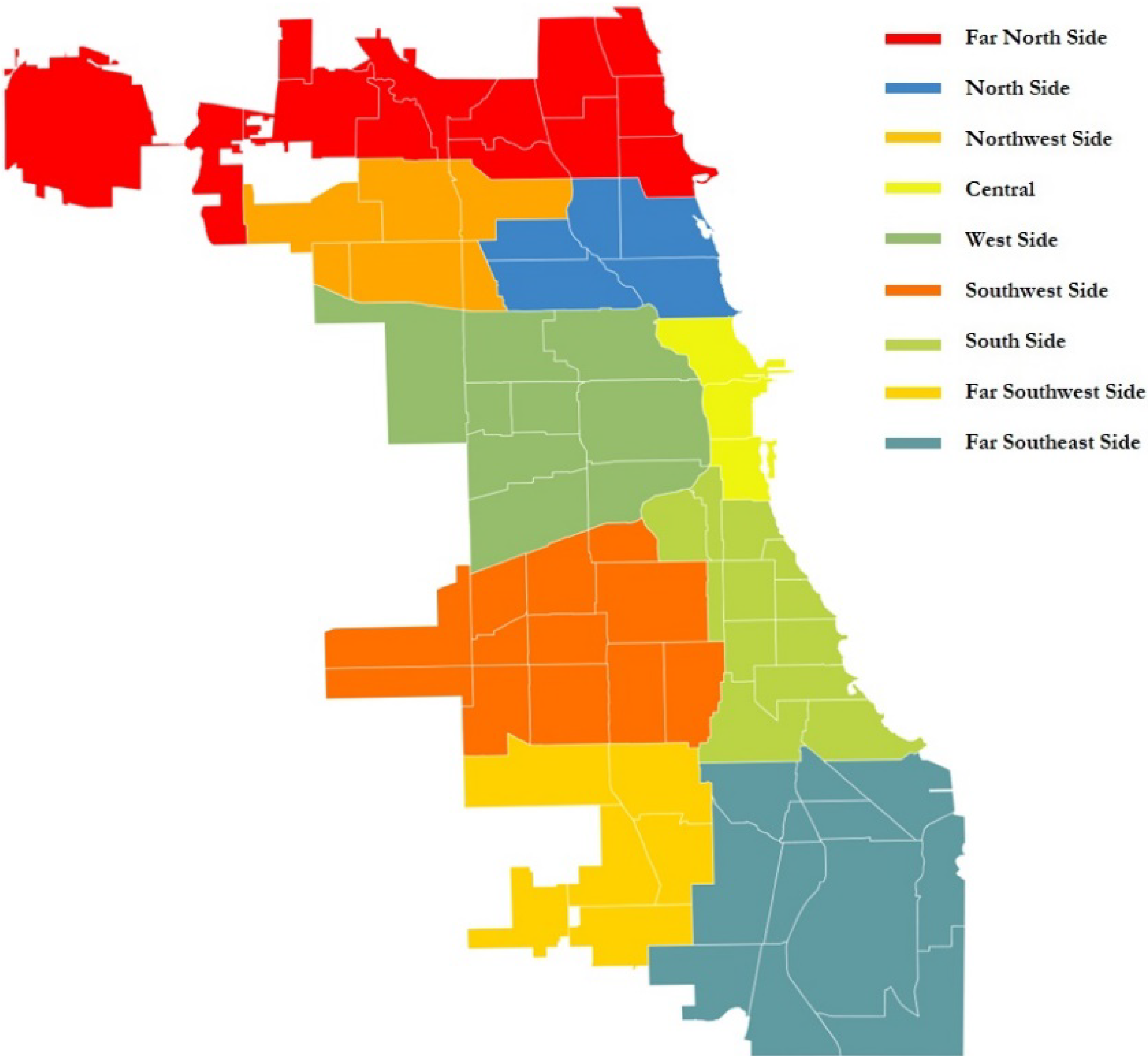

Figure 16.1: Chicago's neighborhoods

Figure 16.2 depicts the spatial distribution of the MAG_{TA} and the MAG_{TW} for 30-minute and 60-minute travel time thresholds across Chicago. As shown, at the 30-minute travel time threshold, the city is almost entirely dominated by auto access except for the central part due to the presence of the Loop. The access gap between transit and auto is smaller in the Central Business District (CBD) and along the transit lines, particularly in the north and northwest sides. The gap becomes narrower with an increase in travel time. On the contrary, looking at the spatial distribution of MAG_{TW}, it is found that the transit effectiveness is the lowest in the CBD. This might be due to the high density of employment in the CBD easing the reach to jobs by walk.

Table 16.2: MAG and access ratio conversion.

MAG range	Access ratio
$[-0.10, -0.75)$	0.0-0.1
$[-0.75, -0.50)$	0.1-0.3
$[-0.50, -0.25)$	0.3-0.6
$[-0.25, 0.00)$	0.6-1.0
$[0.00, 0.25)$	1.0-1.7
$[0.25, 0.50)$	1.7-3.0
$[0.50, 0.75)$	3.0-7.0
$[0.75, 1.0)$	7.0+

Findings

Here, we measure the MAG for Chicago and its nine neighborhoods for all twelve 5-minute travel-time thresholds. Figure 16.3 portrays the variation of MAG over time for transit and auto as well as transit and walk in Chicago. Two conclusions can be drawn. First, the MAG_{TA} indicates that Chicago is an auto-access dominant city, but the degree of the domination is a function of the travel time threshold. With an increase in the travel-time threshold, a gradual improvement in transit access appears, albeit it is meager. For the City of Chicago, the MAG_{TA} begins to become narrower at 25-minute travel time threshold. Second, the positive MAG_{TW} suggests that transit offers better access compared to walk at the city level. While the modal gap between walk and transit is insignificant at shorter travel time thresholds, it increases as travel time increments. The initial small gap is explicable as at shorter travel times a large portion of commuting by transit compose the access and egress which happens to take place by walking. This accentuates that walking is a competitive mode of travel for short trips in Chicago. At shorter travel times, the access ratio of transit to walk at its most is roughly 1.7. After 10 minutes, the modal gap increases drastically, taking away any chance of competitiveness from the walk. With travel time increase, the access ratio reaches its uppermost where transit offers 7 times or more employment opportunities compared to walk. Overall, the trend in both graphs portends that an increase in travel-time thresholds hustles Chicago toward being a less auto-access-oriented city with a more transit

effectiveness. The shift between the number of accessible employment opportunities at different travel time thresholds ratifies that the modal access gap is indeed a function of travel time in the city.

Figure 16.4 portrays the fluctuations in the values of MAG_{TW} and MAG_{TA} over time across nine neighborhoods of Chicago. Two patterns can be discerned. First, in the central area, the trend in modal gap variations over time is anomalous for both MAG_{TW} and MAG_{TA}. Comparing transit and walk, transit access improves with an increase in travel-time thresholds regardless of the neighborhoods. In the Central Business District (CBD), however, transit effectiveness declines with travel time increment. Comparing transit and auto, the CBD shows a significantly less auto-access-orientation. While other neighborhoods display a slow increase in MAG_{TA}, the central demonstrates a rapid transit access improvement over time. We speculate that the distinction of the CBD is associated with high employment density and concentration of transit system in the CBD. Second, the lowest transit access is offered in the far southwest and far southeast sides. In these two areas, comparing transit and walk, MAG_{TW} values are the lowest among all areas. Comparing transit and auto, it is only after the 40-minute travel-time threshold that the transit effectiveness slowly improves at far southwest and far southeast sides. The number of stations in these two neighborhoods although not scant, clearly cannot offer an effective transit service. These two areas are the farthest from the central area as the heart of the city's transit system.

Table 16.3 ranks all 9 neighborhoods by the highest MAG values for 15, 30, 45, and 60-minute travel-time thresholds. As presented, the neighborhoods rankings are not persistent across travel time thresholds. For transit against auto in Table 16.3, the top-ranked area with less auto-oriented design across all travel times is the Central area. In the 15-minute travel-time threshold, the top three areas with the best transit access are Central, Far Southeast Side, and Far North Side. In the 30-minute travel-time threshold, while the Central remains on top, Far Southeast Side falls into the last place overtaken by the North Side. North Side remains among the top three at 30, 45, and 60 minutes. West, at the end of the table, are areas with worse transit services; Far Southwest Side remains at 8th place over all four travel time thresholds, indicating that compared to other areas it has a low transit access and is highly auto-oriented at all travel time thresholds. For transit against walk, in Table 16.3,

Rank	Travel-time Threshold (Minute) 15	30	45	60
		MAG_{TA}		
1	Central	Central	Central	Central
2	Far Southeast Side	North Side	North Side	North Side
3	Far North Side	West Side	South Side	West Side
4	Northwest Side	South Side	West Side	South Side
5	Southwest Side	Far North Side	Southwest Side	Far North Side
6	South Side	Northwest Side	Far North Side	Southwest Side
7	North Side	Far Southwest Side	Northwest Side	Northwest Side
8	Far Southwest Side	Southwest Side	Far Southwest Side	Far Southwest Side
9	West Side	Far Southeast Side	Far Southeast Side	Far Southeast Side
		MAG_{TW}		
	15	**30**	**45**	**60**
1	Central	West Side	South Side	Southwest Side
2	North Side	North Side	Southwest Side	Far Southeast Side
3	West Side	Southwest Side	North Side	South Side
4	South Side	South Side	West Side	Far Southwest Side
5	Far Southeast Side	Northwest Side	Far North Side	Northwest Side
6	Southwest Side	Far North Side	Far Southwest Side	Far North Side
7	Northwest Side	Far Southwest Side	Far Southeast Side	North Side
8	Far North Side	Far Southeast Side	Northwest Side	West Side
9	Far Southwest Side	Central	Central	Central

Table 16.3: Neighborhood ranking by MAG for 15, 30, 45, and 60-minute time thresholds

areas offering better transit access are placed on top. At 15 minutes of travel time, the central and all its adjacent neighborhoods, North, West, and South Sides are placed on top indicating better transit access compared to walk. When travel time increases, however, Central falls into the last place. The drastic transition in central's ranking is due to the spatial characteristics of this restricted area, where it offers better access through the walk at longer travel times compared with transit.

Figure 16.5 illustrates the deviation of MAG at the neighborhood level from the MAG at the city level. Each bar has a lower bound representing a neighborhood with the lowest MAG value, an upper bound referring to a neighborhood with the highest MAG value, and a point between the two extremes presenting the Chicago MAG for the entire city. Two observations are noted: (1) the range of MAG variation and (2) the position of the Chicago's MAG value compared to the upper and lower bounds at different travel time thresholds. In the transit and walk graph, the disparity of MAG_{TW} between upper and lower bounds is insignificant at shorter travel

time thresholds. As travel time increases, each bar exhibits a wider range of MAG_{TW} variation, indicating a higher disparity between neighborhoods' modal gap. The Chicago's MAG_{TW} at shorter travel times stays almost at the middle of each bar. As travel time increases, Chicago's MAG_{TW} skews toward the upper bound and portends a MAG_{TW} value that only represents neighborhoods with greater MAG_{TW} values, and disregards neighborhoods with lower MAG_{TW} values. For transit and auto, a different fashion can be perceived. The range of MAG_{TA} demonstrates an insignificant variation between neighborhoods' MAG_{TA} at shorter travel time thresholds. With an increase in travel time, the disparity of MAG_{TA} between neighborhoods quickly diverges and reaches its utmost at 30-minute travel time. It then gradually starts to converge until tail-end. At shorter travel time thresholds, the Chicago's MAG_{TA} holds a value near lower bounds. This indicates that Chicago's MAG_{TA} is mostly representing neighborhoods with very low modal gaps. With an increase in travel time threshold, the Chicago's MAG_{TA} moves toward the middle. This suggests that at higher travel times, the Chicago's MAG_{TA} is a more sensible representation of the modal gap across the city. Overall, it is understood that the modal access gap at the city level varies from the modal gap across neighborhoods. This variation also exists over time. A sole MAG index for an entire city, therefore, is not a realistic representation for all neighborhoods and across different travel time thresholds.

Our findings offer the disparity of temporal and spatial variants of modal access gap across Chicago and its nine neighborhoods. In the West, South, North, and Southwest sides, transit shows less deviation from auto and more production than walk in offering access to jobs. On the contrary, the farther a neighborhood gets from the central area its transit performance degrades. Far southeast, far southwest, northwest, southwest, and far north sides are highly auto-access-oriented and demonstrate a large modal access gap. In these neighborhoods, the relative access offered by transit is less than 0.1 times by auto.

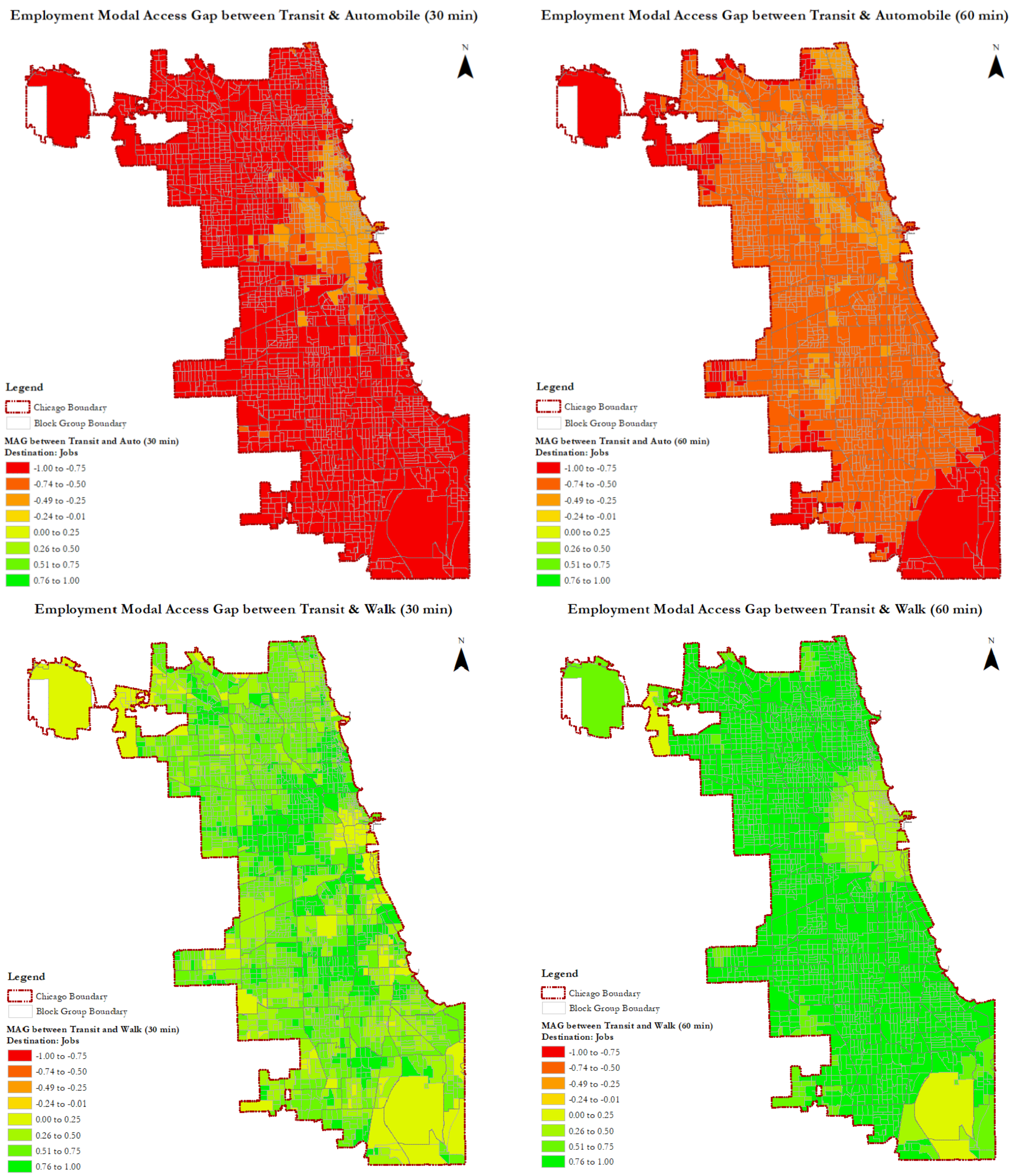

Figure 16.2: Spatial patterns of MAG in Chicago for 30-minute and 60-minute travel time

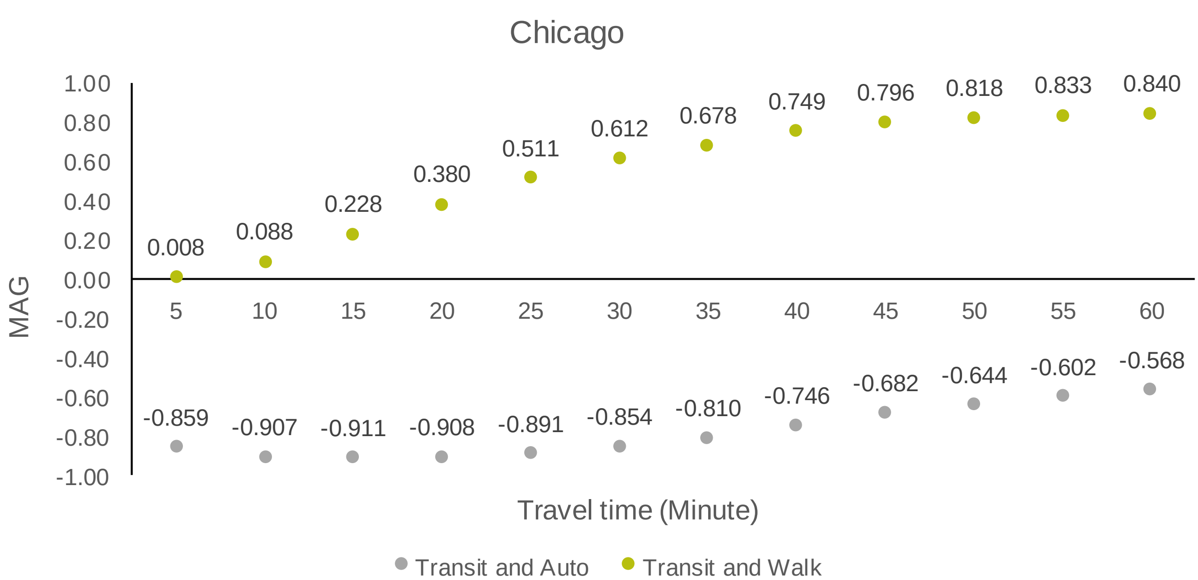

Figure 16.3: Variation of MAG_{TA} and MAG_{TW} over time in Chicago

Figure 16.4: Variation of MAG_{TA} (top) and MAG_{TW} (bottom) over time and space in Chicago

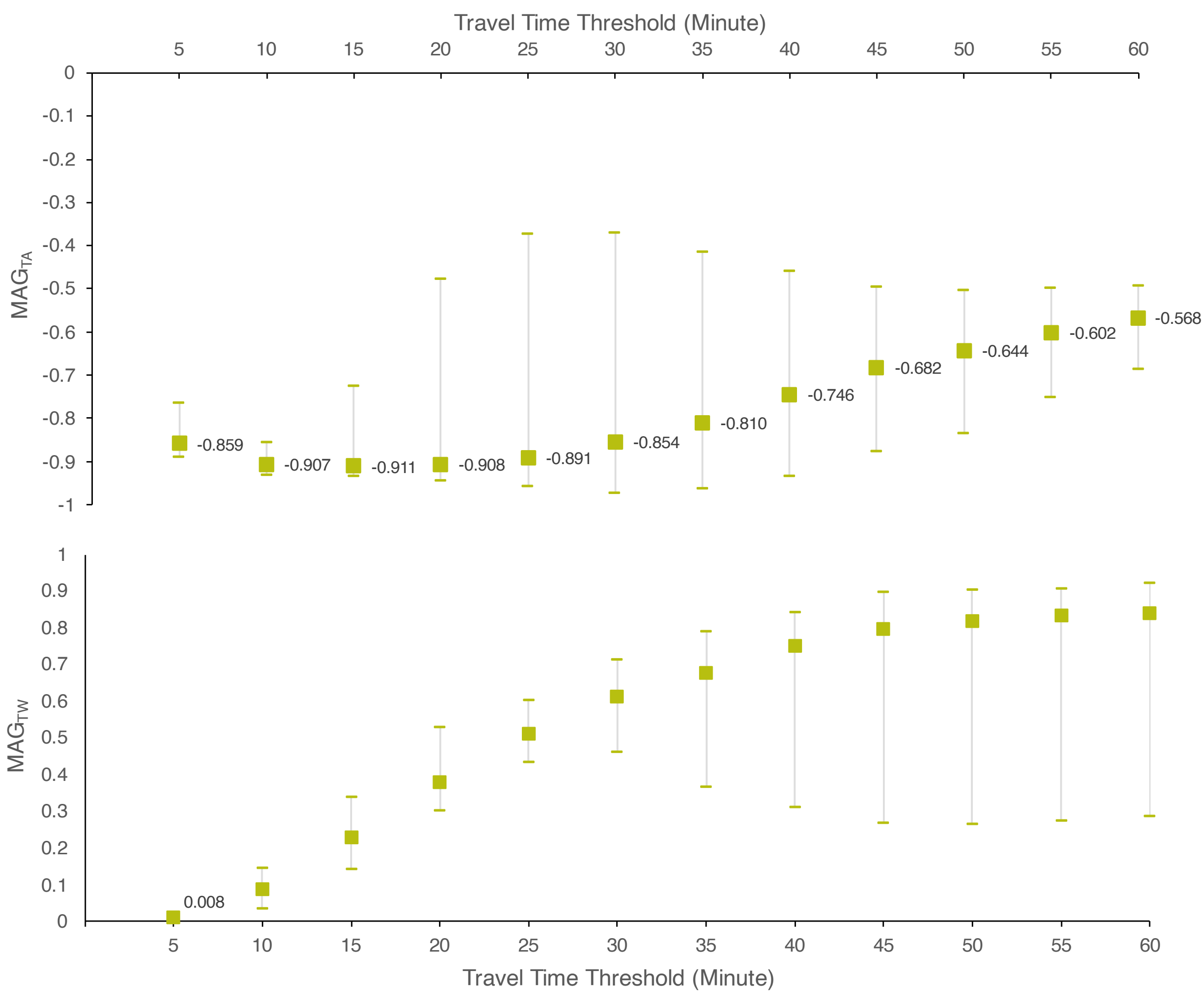

Figure 16.5: Deviation of MAG_{TA} (top) and MAG_{TW} (bottom) of neighborhoods from the city's value for different travel times

Conclusions

This research has analyzed the disparity of access to jobs by transit, auto, and walk at the city-level and neighborhood-level. Through measuring the modal access gap over time and space, we have corroborated that the modal access gap is indeed a function of travel time and location. The findings have indicated that modal access gap varies with changes in travel time. For transit and walk, at shorter travel times the modal gap possessed its minimum value, but with travel time increments the modal gap increased suggesting an improvement in relative transit effectiveness over longer distances. For transit and walk, the variation of MAG over time was different; at shorter travel times there was a considerable modal gap between auto and transit. When travel time increased, the modal gap narrowed implying better transit performance. Overall, with travel time increment, transit performance improves in the City of Chicago. The findings have also indicated that modal access gap varied across neighborhoods. Different neighborhoods, depending on their proximity and distance from the central area, displayed different gap variations. Generally, central neighborhoods had better transit effectiveness. Neighborhoods located farther from the central area showed lower transit efficiency. The central area itself possessed a completely distinct MAG variation.

Employment density in most large cities is higher in central business districts similar to central Chicago. Employment, however, is becoming more decentralized as people tend to relocate to suburban areas.[22] This draws attention to the need to improve suburban transit services. Our analysis has demonstrated that in far north sides, far southwest, and the far southeast side of Chicago, transit system performs less effectively than other sides of the city. By solely measuring access at the city level, low transit access of neighborhoods could have not been recognized. Another interesting interpretation can be drawn from central area analysis. In this area, the ubiquitous transit system was not able to compete with walk after a certain time threshold.

[22] (McMillen and Lester 2003).

This chapter contributed to the access literature by expanding the modal access gap analysis to measure the incongruity of modal gaps for transit, auto, and walk. Analyzing the walk mode assessed transit effectiveness across the city and, more importantly, in the CBD of Chicago. We argued that the modal access gap is a time-variant concept, and its evaluation should not be limited to a single travel

time. Finally, this chapter drew attention to the effect of the scale of analysis on the outcome of access research.[23]

[23] (Biehl et al. 2018).

Next

We speculate in more constrained areas around employment opportunities walk competes with transit, lowering its effectiveness. Hence, avoiding monocentric city planning and disseminating employment activity across the metropolitan area is likely to encourage active commuting. Transit access is also associated with socioeconomic characteristics, particularly race and income.[24] While access measures are scale-variant, to preclude inequality, it is important to consider the state of access across neighborhoods for better and more equitable urban planning. This analysis has been conducted for the primary cost of travel time. Consideration of the private monetary costs, and full social costs of travel may improve the relative performance of walking and public transit.[25]

[24] (Ermagun and Tilahun 2020).

[25] (Cui and Levinson 2018c, El-Geneidy et al. 2016).

The detailed assessments of this research inform both urban planners and policymakers of how neighborhood-level access analysis can depict a different picture of the existing condition and reveal the inequality within a city.

17
Interactive Access for Integrated Planning

Anson Stewart and Andrew Byrd

Abstract: This chapter evaluates how interactive tools for calculating and visualizing indicators of access to opportunities can facilitate more integrated metropolitan planning. Pertinent dimensions include integration between: land-use and transport planning, public transport and other modes, and different tiers of government. In semi-structured interviews, we asked planning professionals in the Netherlands, Melbourne, Montréal, Los Angeles, and Nashville, all of whom use a specific web-based interactive accessibility tool, what integration challenges they face, and how accessibility concepts and interactive tools help them confront these challenges. Abilities to specify new scenarios and alternative indicators, then rapidly re-compute results, facilitate collaboration that can address common obstacles to cross-sectoral/cross-agency collaboration and horizontal integration. In contexts where weak vertical integration creates political challenges, quantitative accessibility indicators can help promote more evidence-driven planning. As specific accessibility indicators are adopted more widely in policy, interactive accessibility tools show promise for facilitating stronger integration, and in turn more efficient and equitable metropolitan regions.

Introduction

Keywords: Accessibility; Collaboration; Metropolitan governance; Interactive web-based tool

This chapter evaluates whether interactive tools for calculating and visualizing indicators of access to opportunities facilitate more integrated metropolitan planning. We use a comparative approach, deriving findings from interviews with planning professionals in a

range of contexts who all use one specific web-based tool for sketch planning and multi-modal access analysis.

Access concepts have been promoted in metropolitan planning for decades, but the use of specific access indicators has been relatively rare even recently. A survey of land use and transport practitioners suggests the mention of access as a concept is more than twice as prevalent as the use of actual indicators, due largely to barriers such as lack of knowledge, data, time, software, and supportive regulatory frameworks.[1] Others have identified theoretical, conceptual, and institutional barriers.[2]

[1] (Boisjoly and El-geneidy 2017).

[2] (Ferreira and Papa 2020, Levine 2020, Miller 2018, Silva et al. 2017).

In recent years, interactive access tools have become readily available, addressing many of these barriers. When deployed as cloud-based web applications, such tools provide practitioners with powerful analysis and scenario planning capabilities, without requiring them to install specialized software. Efficient computation and automatic construction of networks from open data sources reduce the time and expense of training and data preparation. New access handbooks reference such tools,[3] and planning practice now seems to be "on the cusp of an accessibility era."[4]

[3] (Levinson and King 2020, Sundquist et al. 2021).

[4] (Handy 2020: p. 2).

One widely used component for access analysis is R5, open-source software that allows rapid access evaluation, capturing travel time variability, uncertainty, and other details important to multimodal trips.[5] Various extensions to R5 have demonstrated strong computational performance in access analysis.[6]

[5] (Conway et al. 2017; 2018).

[6] See (Conway and Stewart 2019, Saraiva et al. 2020).

The authors have launched and sustained the R5 project over several years with the express purpose of enabling collaborative, integrated land-use and transport planning by operationalizing access concepts in ways appropriate for interactive use. Rather than detailing underlying technical methods (which have been covered elsewhere), this chapter describes how such interactive use has helped planners overcome barriers to integration in metropolitan planning.

Questions

This chapter addresses the following questions:

- Do practitioners in different contexts identify similar types of integration challenges in metropolitan land-use and transport planning?
- Does the concept of access help overcome these challenges?

- Do rapid computation, minimal installation and configuration requirements, and other attributes of the systems described above help reinforce integration?

Integration in metropolitan planning requires collaboration beyond the initial steps of communication, cooperation, and coordination.[7] There are three broad dimensions of integration:

[7] (Zegras 2017).

- vertical, between different levels of government;
- horizontal, between different agencies or departments at a given level; and
- spatial, between neighboring jurisdictions.[8]

[8] (May et al. 2006).

Integration along these dimensions, as well as at operational levels (e.g., across modes and pricing regimes), can lead to improved efficiency. Interactive access tools can help stakeholders develop indicators and "a shared understanding of how... alternatives should be measured and weighed."[9] Such instances of stakeholders from diverse organizational cultures working together to reformulate indicators exemplify "double-loop learning" in governance.[10]

[9] (Stewart and Zegras 2016).

[10] (Moynihan 2005).

In short, this chapter gathers evidence on whether the availability of interactive access tools has encouraged planning processes that are more integrated, both in between different administrative levels (vertical) and across historically distinct disciplines and organizational cultures (horizontal). Our initial expectation is that planners working under varying governance and institutional arrangements will identify similar challenges, and similar ways that access tools have helped them advance integration in land-use and multi-modal transport planning.

This expectation is founded on two mechanisms. First, the concept of access, which inherently integrates data on demographics, land-use, and transport, can help convene stakeholders with different priorities and backgrounds. Then, once they are at the table, interactive tools can reduce communication barriers and keep them engaged.

Methods

We employ a comparative method, drawing on semi-structured interviews with planning professionals who are active users of

Conveyal's cloud-hosted deployment of R5 for access analysis. These practitioners are based in five metropolitan contexts:

- Netherlands: consultants with a Dutch firm discussing planning projects in the Randstad (approximate population: 7 million),
- Melbourne, Victoria, Australia: planner with the state authority responsible for strategic land-use and infrastructure planning in Greater Melbourne (population: 4.7 million) and the remainder of the state of Victoria,
- Montréal, Québec, Canada: planner with the transport authority for the metropolitan region (population: 4.1 million),
- Los Angeles, California, United States: planner with the city DOT (city population: 4.0 million, metro area population: 13.1 million), and
- Nashville, Tennessee, United States: planner with the transit planning and operating agency for metropolitan Nashville and Davidson County (population 700 thousand).

We selected these contexts to be diverse along relevant dimensions of integration. In terms of spatial and operational integration, for example, public transport in Nashville is almost entirely bus-based, with two public-sector operators, while public transport in the Netherlands is highly multimodal, with the busiest rail network in the EU and integrated nationwide payment and scheduling.[11] Greater Montréal has tiers of local, municipal, metropolitan, and provincial entities with planning powers, while Melbourne has only the local council and state levels.

[11] (Kjeldmark 2020).

As discussed in the Findings section, authorities in all five contexts have framed planning in terms of access concepts, but on varying timelines. The Netherlands has a decades-long history of integrated planning with progressive adoption of access planning in certain metropolitan regions; the Australian focus on 20/30-minute cities is much newer. All five contexts also have recent examples of using the same shared computational platform and formulating specific access indicators to guide decision making.

We sent each respondent this list of questions:

- [List of example documents/reports relevant to region] Can you share additional examples of policy guidance or planning documents illustrating equity, health, and system performance goals for metropolitan planning in your region?

- What are 2-3 main challenges your organization faces with respect to integrated planning at the metropolitan scale? Examples might include integration across domains (e.g., land-use and transport), jurisdictions, organizational entities (e.g., different departments within a city), or transport modes.
  - How does the concept of access to opportunities help you confront these challenges?
  - How do cloud-hosted platforms help you confront these challenges?
- How do you integrate this specific cloud-based platform with existing external workflows? Has it allowed you to create new planning or analysis processes?
- What are breakpoints in your timelines for feedback, interaction, and collaboration? For example, do prospects for successful integrated planning change markedly if interaction takes longer than seconds/hours/months?

These questions are intended to prompt discussion of multiple aspects and dimensions of integration.

Findings

Multiple respondents from the Netherlands replied both in writing and in follow-up semi-structured interviews. Each of the other four regions had one respondent; three participated in semi-structured videoconference interviews, and one replied in writing. In this section we first describe the five regions and discuss the interview responses, supplementing with background from public planning documents and our experience collaborating with the organizations. The remaining three subsections synthesize the findings across these contexts.

Netherlands

Our respondents in the Netherlands are public transport and land use planning consultants at Movares Nederland BV, a consulting and engineering firm now handling a broad range of subjects, but with a strong historical connection to passenger rail engineering. Movares has applied and contributed to the development of this access analysis system for over six years, and our primary

respondent now serves as the project lead and internal advocate for this approach within the organization. Movares has used this tool in several integrated planning exercises including the 2040 Public Transport Vision for the metropolitan regions of Amsterdam and the South Randstad (Rotterdam and The Hague), designed to incorporate ideas and priorities sourced from local and municipal stakeholders into regional and finally national policy documents.[12]

[12] See Conway et al. (2017) for a detailed description of this process and how specific transit scenarios were formulated and combined into packages based on iterative access analysis.

The Netherlands has a long history of integration in planning policy, but transition to the use of integrated transport and land use indicators (both relative scenario comparison and absolute objectives) is ongoing, with some regions leading the shift.

Though national policy tends to set more infrastructure-oriented benchmarks, one observatory (the CROW Door-to-Door Dashboard) has chosen to characterize the joint transport and land-use system through cumulative opportunities measures.[13] Access indicators were not an original requirement, but planners who participated in the aforementioned Amsterdam work were able to push for their inclusion. As conditions change from year to year, cloud computation capabilities are used to update interactive websites for millions of origins throughout the country, and national research and policy entities have sponsored a multi-year performance evaluation focused on multimodal – cycling plus transit – access to jobs.

[13] See chapter 1 in this volume.

Interview responses indicate that although national policy goals and institutions are increasingly horizontally integrated, cooperation between land use and spatial planning organizations remains challenging. On the other hand, vertical integration is highly developed, and in many planning processes it is common for meetings to include representatives of local, municipal, regional, and national scale organizations, as well as transport operators.

Even where the use of access indicators has gained currency, the exact definition of indicators is up for discussion as they are rarely specified in policy documents.

Travel time thresholds as well as the mix of work, education, health care, retail, and leisure opportunities to include are still subject to debate. Here, respondents indicate that the ability to quickly and interactively change parameters of the analysis and update visualizations while discussing with participants is key in constructing a shared understanding of the effects of different planning scenarios on the population through a consensus on indicators.

Cooperation between organizations is catalyzed by constructing a framework together, rather than simply conforming to one imposed from the outside, an example of the "double-loop learning" described above.

Many municipalities in the Netherlands have policy objectives that all residents should be within a certain walking or cycling distance or time of public transit or city centers. These existing requirements can be tested more accurately with a system that considers true network travel time under alternative scenarios, as opposed to straight line distance - especially in locales with numerous canals, bridges, highways, and other breaks in the urban fabric.

Access analysis is perceived as a complement to traditional traffic modeling that inspires greater confidence and understanding. Respondents indicated that interactive access visualizations greatly increased interest and enthusiasm surrounding vertically integrated planning meetings. Planners take care to consider large, costly infrastructure projects from multiple angles, but in the absence of other evidence there is a tendency to fall back on classic four-step models or their more sophisticated successors. While the outputs of these models provide one valuable perspective on impacts, they are frequently not well received by participants in planning processes due to a lack of transparency. When participants notice unusual or surprising outputs from classic models, it is often difficult to determine the source of these discrepancies, casting doubt on the meaning and accuracy of results. Naturally participants will then question the inner workings of the model, but answers about its assumptions and parameters are not readily available, reducing confidence in any conclusions and decisions that follow.

Updating such models and generating new results can take weeks of effort, making it impractical for participants to gain hands-on experience of how the models react to various parameters. By contrast, when access indicators are visualized immediately and interactively, participants can verify their characteristics and build consensus around how they should be used and interpreted. While indicators of potential access lack some aspects of classic models – notably capacity limitations and ridership projections, which require behavioral prediction – they are able to maintain the confidence of stakeholders when subjected to direct scrutiny and manipulation. In this way these tools fit into and improve existing model-centric workflows.

Our primary respondent concluded that this approach "plays a huge role in keeping everyone informed and making people enthusiastic to participate in work [and brainstorming sessions]. Because [these tools] run quickly and the results are both objective and easy to understand, everyone involved [understands] what is going on and/or is challenged to come up with new ideas." The team leading a planning process can keep participants informed through regular meetings with up to date access results as scenarios evolve, allowing people to share ideas and ask questions more freely.

Horizontal integration can still be challenging. There is reportedly a tendency toward a sort of unidirectional coordination, where the influence of transport considerations on spatial planning is stronger than the reverse. The progressive unification of planning policy goals at higher levels of government has apparently not yet led to frequent presence of both transport and spatial planning professionals in joint meetings.

Historically the Netherlands has a high degree of vertical integration, which interviewees attributed to the scarcity of land and the need to consider the needs of many people in close proximity. This integration is reflected by the presence of representatives from all levels in planning processes. The use of interactive access visualizations can apparently elevate this formal cooperation to more substantive coordination and integration, founded on the construction of shared interpretive frameworks.

Melbourne

A successor to the planning authority for suburban growth corridors, the Victorian Planning Authority (VPA) was established in 2017 as a state authority, reporting to the Minister for Planning. It is now responsible for strategic land-use and infrastructure planning for both greenfield and urban redevelopment projects. Melbourne lacks a metropolitan authority, so land-use and transport planning responsibilities are split horizontally between separate state departments, and vertically between the state and local councils.

The Plan Melbourne 2017-2050 strategy and implementation plan, and a 2019 addendum, guide VPA's planning efforts. These documents are structured around nine principles and seven outcomes, along with associated policies, many of which invoke

access concepts. A central principle is the "20-minute neighborhood," that residents can meet everyday, non-work needs – "schools, shops, meeting places, open spaces, cafes, doctors, childcare, and access to public transport" – by a walking, cycling, or local public transport round-trip not exceeding 20 minutes.

The 2019 Plan Melbourne addendum describes initial efforts to embed the 20-minute neighborhood principle in planning for major infrastructure projects, with the aim of ensuring "that surrounding communities benefit from the coordinated planning of state and local infrastructure." Policies supporting other relevant outcomes include supporting new housing "in activity centres and other places that offer good access to jobs, services and public transport," developing "an integrated transport system that connects people to jobs and services and goods to market," and providing "high-quality public transport access to job-rich areas."

VPA staff have used cloud-hosted interactive access software since early 2020, tying results into their Development Scenario Modelling workflow, a new multi-criteria assessment for assessing activity centres, and analyses of relationships between development, density, employment types, access, and land value. Detailed walking and cycling analysis allows them to operationalise indicators in support of the 20-minute neighborhood principle.

Montréal

The Regional Metropolitan Transport Authority (ARTM) is responsible for planning, funding, organizing, and promoting public transport in Greater Montréal. An separate intergovernmental organization, the Communauté Métropolitaine de Montréal (CMM), coordinates broader regional planning and economic development for the region's 82 municipalities.[14] ARTM's board is split between CMM and provincial appointees, who are generally independent scientific and private-sector experts, and municipal elected officials. ARTM administers the region's vehicle registration fees and intergovernmental subsidies and grants. It conducts planning for the region's public transport operating organizations, including exo (regional rail), suburban buses, STM (Montréal Metro and bus), and CDPQ Infra, a provincial authority managing the automated regional light rail system (REM) currently under construction. ARTM's strategic plans, which dovetail with CMM's wider regional development planning, are subject to 2/3

14 (Taylor 2020).

[15] (Taylor 2020).

majority approval by the CMM board.[15] Some projects in advanced planning or execution have been delegated to STM. From its position between below the provincial government and above multiple levels of local government and transit operators, ARTM's integration challenges are primarily vertical, and to some extent horizontal in light of CDPQ's planning efforts around regional rail lines.

The public transport strategic development plan (PSD) released in October 2020 elaborates six strategies. The first two are "organize mobility around a structural public transit network" and "align public transit with land use and development," highlighting desired integration with CMM's regional land-use planning. The PSD promotes benefits such as higher mode share for sustainable modes, improved travel opportunities and communities, including "access to activity centres and communities via public transit in less than 45 minutes," and other environmental and economic benefits. It thus provides the basis for concrete access indicators to guide project development. Momentum for this explicit access framing has built over multiple years, driven in part by an academic access expert who serves on the ARTM board, and associated researchers and graduates who have built a critical mass of access expertise at the authority.

Given the adopted access goals, ARTM staff thoroughly evaluated multiple software options for access planning over the course of 2020. Their decision prioritized an option that could build multi-modal networks automatically and be ready for use immediately. General purpose GIS and network analysis tools would have required extensive effort by specialists to prepare inputs, which a peer review suggested would delay planning efforts by 3-6 months; in-house tools or custom deployments were deemed to have risks related to errors, low replicability, and staff continuity. Staff expect the cloud-based platform will let them test multiple scenarios easily, exploring sketch plans for corridors at a high level and obtaining related access indicators, in ways that complement their use of existing demand and transit assignment models.

Los Angeles

The primary guiding document for the Los Angeles Department of Transportation (LADOT) is *Mobility Plan 2035*, which was adopted by the Los Angeles City Council in 2016. The plan effectively

cemented a broader mission and vision for LADOT, to encompass dignity, equity, and access to basic needs. LADOT's traditional involvement in intergovernmental and development review processes tended to be narrowly scoped to questions of traffic modeling and engineering. For example, agency responses a transit corridor plan from the county transport authority (Metro), or to a mixed-use development proposal, would focus on metrics of vehicle delay (such as intersection level-of-service). Prior to *Mobility Plan 2035*, prevailing policy did not encourage asking deeper questions about peoples' safety or travel needs and desires.

After the adoption of *Mobility Plan 2035*, the planning division within LADOT looked to access as 'a language' for considering broader goals. One of the five central priorities of the plan is "Access for All Angelenos: increasing access through greater community connections." In 2019, the planning division solicited a three-year subscription to an access analysis platform,[16] as a tool for decision-support and communication with other agencies. Specifically, the agency desired a tool that would help quantify and communicate how various projects (e.g., densification, targeting investments in specific corridors) would move the needle on larger policy goals. Such quantification was seen as an important way to provide more "policy credibility" for the agency in advancing its broader goals and assessing tradeoffs. Access is also seen as an important concept for engaging with Metro, especially as Metro has increasingly made an equity framework central to its work; LADOT can provide feedback on transit alternatives, drawing on detailed demographic breakdowns of access and assessments of tradeoffs. Such breakdowns include population by quartile of the California Healthy Places Index, which helps highlight impacts on people who live in communities that have been burdened by past planning and policymaking.

[16] See Levinson and King (2020) Appendix G.

Nashville

Nashville MTA, which recently rebranded its services as WeGo Transit, plans and operates public transport as a department of the Metropolitan Government of Nashville and Davidson County, a city-county government consolidated in 1963. Metro Nashville has an elected mayor and vice-mayor, and a Council consisting of 35 district representatives and 5 at-large representatives. This governance structure facilitates vertical integration within the

MTA's service area. While Metro Nashville has public works and public transport departments, the lack of a coordinating transport department impedes horizontal integration. A separate entity, the Middle Tennessee Regional Transportation Authority (RTA), operates bus and commuter rail between Metro Nashville-Davidson and the surrounding eight counties.[17]

[17] See (Fischer et al. 2021).

The RTA and MTA jointly prepared a Regional Transit Plan in 2016. It included service improvement recommendations, general objectives, and five overarching aims, the first of which is "improve access to opportunity for those with limited auto availability." Yet the specific benefits described center ridership and proximity-based measures (e.g., jobs within one-half mile of transit service), rather than indicators of access to opportunity. A 2018 referendum to fund many of the recommendations in this plan failed to pass after being championed by a previous Mayor.[18]

[18] (Accuardi 2019).

In December 2020, the new Mayor won Council approval for a revised Metro Nashville Transportation Plan. A major component was the WeGo Public Transit "Better Bus" program, which includes span-of-service and frequency improvements, new orbital routes, and coordination with transport network companies to provide on-demand service as a first/last-mile complement to fixed-route service. This feeder service gives passengers rides between designated transit centers and areas nearby, with guaranteed maximum waiting times. Using the access platform since 2018, MTA planners iterated through combinations of on-demand service areas, route alignments, frequency modifications, span-of-service changes as the plan evolved. Iterative access analysis allowed specific cumulative opportunities measures[19] to be a factor guiding decision making. In addition to employment access, planners conducted equity analyses of impacts on different demographic groups of current riders, pairing travel time outputs from R5 with on-board survey responses. As scenarios were finalized, results were published to an interactive portal that allowed the general public to see the impact on their specific commutes, linking system performance metrics with stakeholder engagement.

[19] See chapter 1 in this volume.

Better Bus materials published in 2020 promote notably different benefits than the 2016 plan. They include refined proximity-based metrics, such as the percent of the population that has access to service within various frequency tiers, for various demographic groups and affordable housing clusters. Following these metrics is a pivot to access: "But Better Bus is not just about having access to

better service. Ultimately, it's about where that service can take you and how it can connect you with the rest of your life." A set of isochrone maps, showing the area reachable within 60 minutes of door-to-door travel time (including walking along the network and waiting) under the baseline and proposed scenario, emphasizes the point of expanded access to the places people want to reach (Figure 17.1).

The public materials let people explore access interactively. In the example shown in Figure 17.2, for weekday evening travel from an origin in Old Hickory to a destination on Oakwood Avenue:

- The baseline scenario involves riding routes 76 and 56, requiring 92 minutes of waiting, walking, and riding time. A 60-minute isochrone, shown in red, falls well short of the selected destination and contains 4.5 thousand jobs.

- The Better Bus scenario allows riding the newly added Old Hickory on-demand service (MOD) and crosstown route (Trinity), reducing the total travel time by 26 minutes. A 60-minute isochrone for this scenario, shown in blue, contains over 6 times more jobs. The isochrone reflects available on-demand service from the origin to fixed-route transit stops at Madison and Hermitage Hills.

Thanks to efficient pre-computation, results for other origins, destinations, time cutoffs, and times of day are available nearly instantaneously.

Integration challenges

Across contexts, respondents indeed identified similar challenges with respect to integrated metropolitan planning.

All respondents identified horizontal integration issues. Unsurprisingly, divisions between land-use and transport "silos" were often a challenge. The VPA, for example, generally relies on the state department of transport and their consultants to run transport models, which hampers integration because of time, cost, and the lack of transparency in black-box models. Planners in the Netherlands similarly identified the ingrained use of opaque models with long running times as a challenge. Even with strong communication and cooperation at individual and organizational levels, these traditional computational limitations impede steps toward coordination and integration. Respondents in Nashville and

the Netherlands identified housing scarcity and unaffordability as pressing issues. Transport has a role to play, but land-use may be able to move the needle more effectively.

"Unidirectional" coordination, with pre-determined transport decisions driving spatial planning, was another common challenge. ARTM's charge to align transport and land-use with the new regional rail lines is a prime example,[20] which raises horizontal integration issues even between two organizations focused on transport.

[20] (Blumgart 2021).

In terms of vertical issues, a common challenge was communicating with elected officials accountable to state or local constituencies, rather than metropolitan ones. Melbourne lacks any metropolitan governance, so state-level officials often dictate project priorities. Even with the metropolitan governance authorities in Montréal, political priorities from the provincial level tend to play a dominant role in prioritizing projects. Planners in Nashville need to build political will with the 35 district councilors, in addition to the Metro mayor. In short, a challenge for metropolitan planning has been meeting the demands of election cycles and different levels of government. Respondents in the Netherlands did not identify such salient challenges, perhaps thanks to a long history of coordinated governance and vertical integration.

Role of access

The responses described above suggest that access can help planners confront obstacles to integration by providing a conceptual link between transport and the concerns of planners and decisionmakers in other organizations. This conceptual link is especially strong in contexts where access has been adopted as a central policy principle (e.g., Melbourne and some regions in the Netherlands). On the other hand, simpler measures of proximity to stops or infrastructure were still prominent as easily graspable concepts to communicate to stakeholders in multiple contexts. And ridership projections were still featured prominently, especially for capital projects in the United States, where federal funding is largely contingent on estimated ridership.

There are also examples of communication fostered by access concepts, even in contexts where formalized access policy goals are still nascent. Our respondent in Los Angeles specifically recognized the desire for "frameworks like accessibility to give us a language."

In Montréal, recent municipal policy initiatives have focused on community health for vulnerable populations; the ability to frame transport projects in terms of access to healthcare and other services for communities of concern is a potential point of connection for ARTM to strengthen communication with municipal officials responsible for these initiatives, crossing both horizontal and vertical barriers. While housing is beyond the Nashville MTA's remit, ready access to isochrone mapping and access tools allows them to have substantive conversations with other agencies focused on affordable housing, and identify where policy levers other than transit service may be more effective. Similarly, MTA staff communicate regularly with colleagues in the Metro planning department's travel demand management team, providing them with detailed multimodal isochrones that inform custom workforce access analyses for large employers.

While our interview question was about "the concept of access," respondents also highlighted the role that specific indicators play in informing evidence-driven planning. In Nashville, sharing quantitative access results and maps for specific neighborhoods and districts was a useful tactic to address the multiple constituencies in the region's vertical governance. Especially in Montréal and Melbourne, the ability to derive holistic, quantitative measures of impact early in the project development process was seen as an important response to political mandates (pre-)ordaining certain projects. In these contexts and in the Netherlands, the ability to specify and compute quantitative indicators interactively was a useful complement to the demand models that have traditionally provided the primary evidence base for transport planning.

Role of interactivity

Traditional transport modeling tools can take hours to converge, so they are often configured for overnight runs on dedicated computing equipment. Respondents noted that these timelines impede iterative analysis and collaboration. In contrast, the access tool used by our respondents handles access by multiple transport modes at high resolutions and for large geographies in seconds. Most respondents agreed on turnaround-time breakpoints for three use cases. For internal access analysis by staff, the ability to run a comprehensive regionwide analysis in a few minutes, and definitely under an hour, was critical. For interactive work sessions with

multiple stakeholders, which some respondents regularly run and others are considering, the ability to re-compute access in a few seconds, for different scenarios, locations, or re-specified indicators, was deemed critical. A third critical turnaround time, fractions of a second, was identified for high-level decision makers and members of the public who are accustomed to highly responsive consumer web applications.

In addition to rapid computation, respondents noted a few other practical advantages of a hosted application for access analysis. Easy account setup and access through a web browser lowered barriers to entry, allowing broader collaboration. LADOT in particular noted the importance of avoiding dedicated workstations and rigid licenses. Our respondent again used metaphors of language, noting that shared online accounts were nimble and allowed diverse users to develop "fluency" through continual exposure to the platform and be "conversant" about how access can inform a wide range of projects. The incorporation of multiple modes, including walking, cycling, public transport, and on-demand modes, in a single analysis tool with results that were easy to inspect interactively, helped stakeholders from multiple departments and levels of government participate enthusiastically, without feeling intimidated by black-box models.

Conclusions

Past research has considered institutional barriers to the adoption of access planning.[21] We flipped this question, investigating how access tools now being used in practice can address institutional and other integration challenges. Our cases suggest that interactive, cloud-hosted software for access analysis facilitates multiple dimensions of integration. Collaboration using interactive tools can reduce barriers to coordinated planning between different agencies, levels of government, and bureaucratic silos. In the diverse contexts we compare, the ability to calculate highly detailed and customizable access measures, iteratively and rapidly, opened the door to workflows and collaboration that were previously prohibitive in terms of effort required.

[21] (Ferreira and Papa 2020).

For practitioners, this chapter has a number of takeaways. Our respondents identified connections to salient themes of equity, housing affordability, and community health. Customized access indicators can quantify transport project impacts in ways that

connect to these themes, helping bring stakeholders to the table. Our findings suggest that once relevant stakeholders have convened, rapid-turnaround and easy to interrogate tools help keep them engaged. Interactive access tools facilitate not only computing more detailed indicators, but allowing stakeholders and the public to explore them in intuitive, customizable ways.

Finally, it may not be necessary to have a specific indicator formulated and enshrined in policy guidance before convening stakeholders. An example is the ongoing debate in the Netherlands about which destination types to include in access metrics, and how to weight them. Another example is the need to select appropriate travel time cutoffs when communicating with elected officials representing different rings of Metro Nashville. The *ad hoc* nature of access measures, with different specifications being used in different cases, has been identified as a challenge to overcome.[22] Perhaps it is also an opportunity, and the ability to customize indicators for specific applications promotes "double-loop learning" in action. A flexible access tool allows planners to reformulate indicators quickly and collaboratively, following the same general form but customizing as needed in response to different settings, emerging research, and evolving values. Especially as planners and policymakers face stronger mandates for equity and efficiency in metropolitan regions, interactive access analysis shows promise for engaging diverse stakeholders in coordinated action.

[22] (Miller 2018).

Next

In terms of future research in access methods and policy, new ways of calibrating impedance/decay function parameters are being developed,[23] which could inform the use of such functions in these tools. Multi-faceted access indicators, such as the joint 20-minute towns (access to various neighborhood amenities) and 45-minute city (access to the regional labor market) promised by Singapore's latest Land Transport Master Plan, are increasingly common and could be backed by further research into how different indicators can be combined into holistic indexes. As further research clarifies links between access, economic productivity, and environmental impacts – through relationships with mode share and vehicle-miles traveled, for example – access planning will become even more relevant.

[23] e.g., (Merlin 2020).

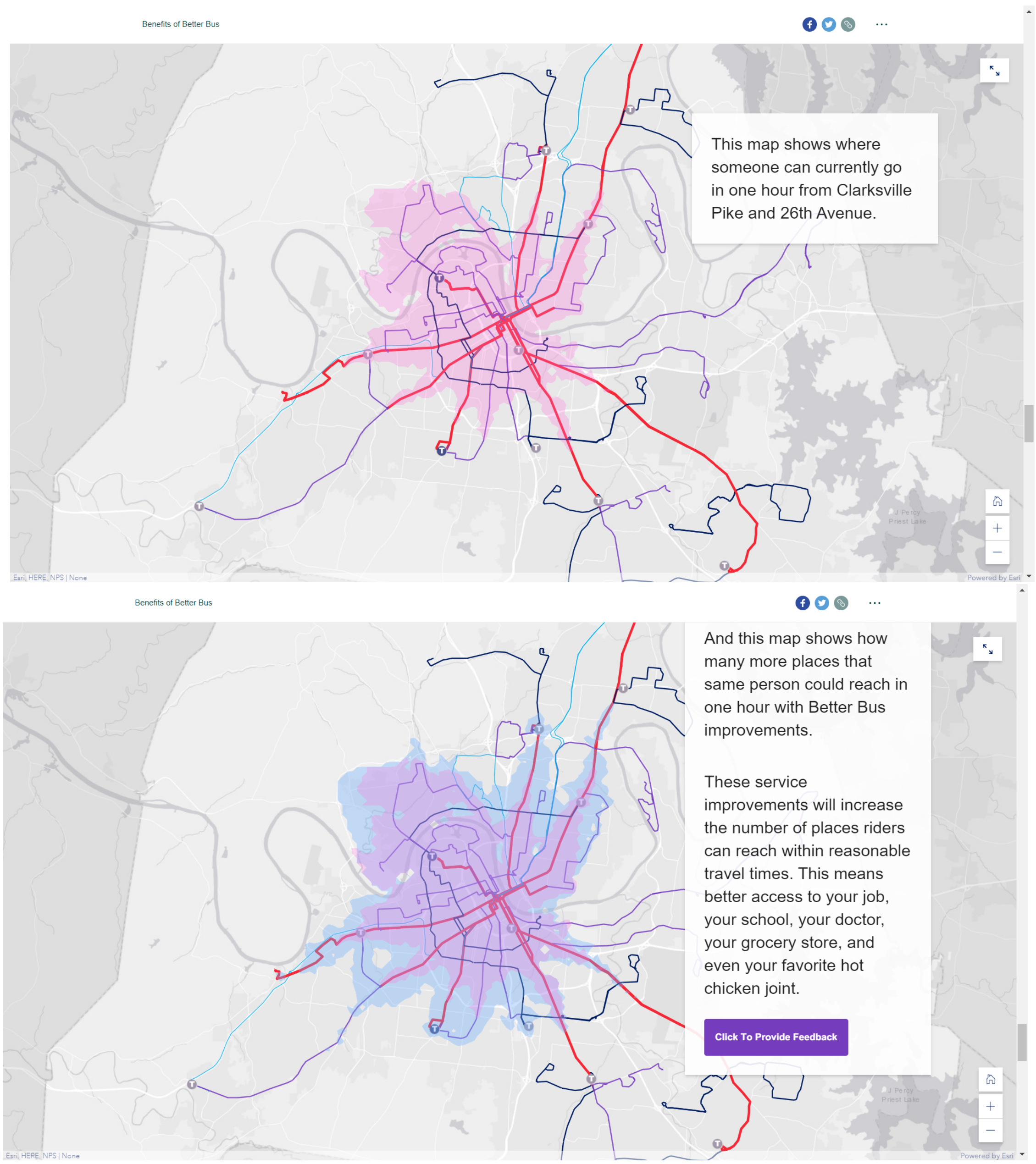

Figure 17.1: Isochrone maps in the Better Bus plan, comparing access under the baseline and proposed scenarios

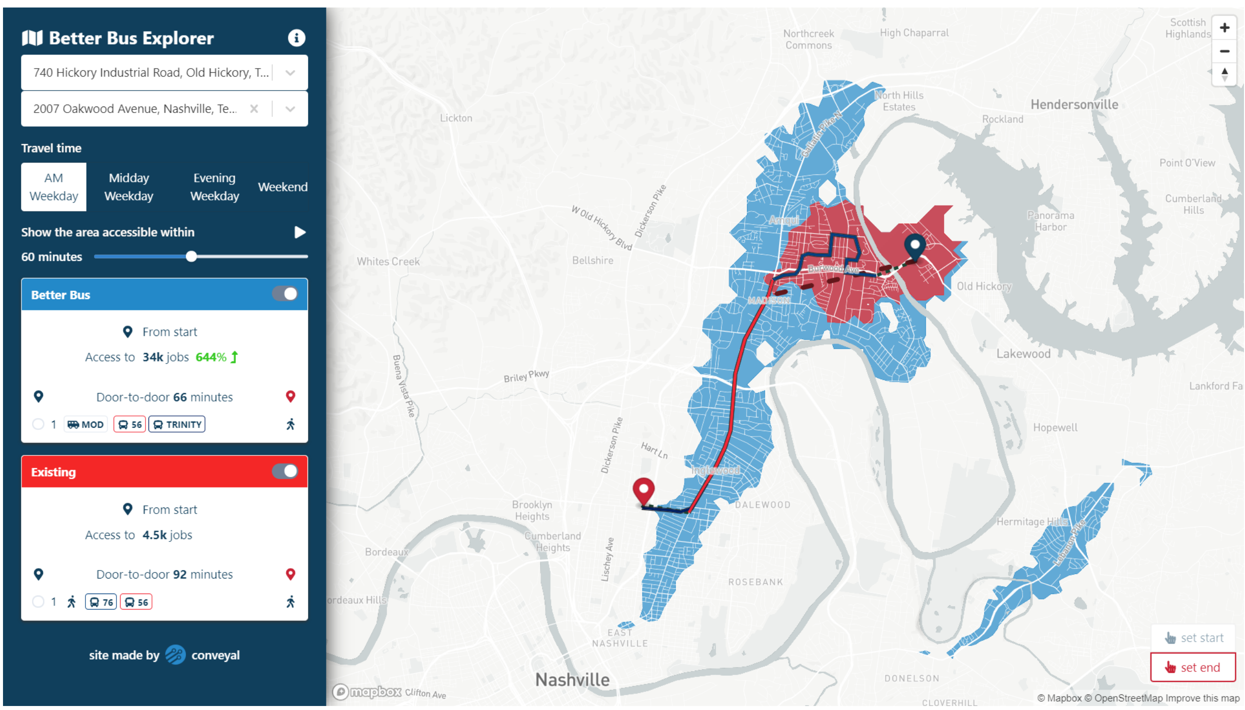

Figure 17.2: Screenshot from the WeGo Transit Better Bus Explorer, comparing access to jobs from a specific origin and times to a specific destination

18
The Role of Transit Service Area Definition for Access-based Evaluation

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Abstract: This chapter examines the importance of service area definition, when utilizing access-based evaluation in transit projects. We analyze two transit projects: (1) Metro Transit A Line in Minnesota and (2) Harris County Transit Re-Imagined Bus Network in Texas. The results indicate that the choice of transit service areas has a significant impact on the value of absolute access measures. The trend shows the narrower the service area, the higher the value of the absolute access measure. The results, however, are inconsistent between projects when relative access measures such as percentage change between scenarios is used as an access-based evaluation measure. We conclude service area definition is of only moderate importance for scenario comparisons within the same analysis boundary. When comparing different regions or areas within different boundaries, the service area definition could have a significant impact on all results. This is case-dependent and varies from project to project, which requires calculating both the absolute and relative access measures in an access-based evaluation. In addition, decomposing the access changes in the separate portions of transit projects reveals that the light rail investments have negligible impacts on access levels, while restructuring of the bus network has a slight positive impact on access levels.

Introduction

Keywords: Access; Transit evaluation; Service area; Modifiable areal unit problem (MAUP)

The evaluation criteria of transport investments and transport dimensions of land-use developments is shifting from a mobility-base to an access-base, as the purpose of travel is mainly reaching a destination rather than movement.[1] Access, by definition, refers to the ease of reaching valued destinations, which varies according to transport modes, times of day, and types of destinations. Measurements have been introduced to calculate access, including space-time, utility-based, gravity-based, travel impediment, network measures, and cumulative opportunities.[2]

Although access measurements differ, defining the zone of measurement and transit service area are the building blocks of all the methods in access-based evaluation of transit projects.[3] The zone is generally selected according to data availability and quality, but not because they are fundamentally appropriate units. This varies from standard units such as traffic analysis zone,[4] census tract,[5] census block groups,[6] and census block,[7] to subjective units such as 200×200 grid,[8] and 50×50 grid.[9] The service area, however, defines a neighborhood as a radius around a project location, in which the access is measured to assess transport service quality and performance. The access measure is typically altered using different zone and service area definitions.[10] This sensitivity of access measures to the definition of the zone and service area is referred to as the modifiable areal unit problem (MAUP) in geographical literature.[11]

The term MAUP[12] consists of two primary components: scaling and zoning. Scaling concerns obtaining inconsistent analytical results when using data gathered at different spatial aggregation schemes. Zoning concerns how differing boundaries, even at similar aggregation scales, alter analytical results. When access-based evaluation is employed to assess transit projects, planners and advocates face three basic questions concerning access calculation.

1. What is the appropriate unit of analysis to measure access?
2. What service area should be selected to represent access to the transit system?
3. How and to what extent do the separate portions of transit projects affect the access measure?

In an attempt to answer the first question,[13] selected a buffer of

[1] (Ermagun 2021). Also see chapter 14.

[2] (Páez et al. 2012).

[3] (Horner and Murray 2004).

[4] (Alam et al. 2010).

[5] (Huang and Wei 2002).

[6] See chapter 4 in this volume.

[7] See chapter 14 in this volume.

[8] (Li et al. 2011).

[9] (Yigitcanlar et al. 2007).

[10] (Ortega et al. 2014).

[11] (Fotheringham and Wong 1991).

[12] Coined by (Openshaw and Taylor 1979).

[13] (Horner and Murray 2004).

400m as the service area around the bus-transit in Upper Arlington, a small suburban municipality near the City of Columbus, Ohio. Comparing blocks, block groups, and tracts as different units of analysis to measure access, they found the smaller the unit of analysis, the better the results. However, this requires more sophisticated estimation techniques. In a similar attempt,[14] selected a buffer of 400m as the service area around the bus stops, and studied how the MAUP affects assessment of access in the City of Windsor, Canada. Using 6 different units of analysis, including census tracts, dissemination areas, dissemination blocks, 0.6 km, 0.3 km, and 0.15 km grids, the results recommended using disaggregate data for access measurement to deal with the MAUP phenomenon. Little is known about how and to what extent the service area variation along with the separate portions of transit projects affect the access measure. The second and third questions have remained unanswered in evaluation of transit projects.

[14] (Wan 2016).

This chapter overcomes this lack of knowledge by testing the effects of analysis boundaries on access measurement for two transit projects: (1) Metro Transit A Line in Minnesota and (2) Harris County Transit Re-Imagined Bus Network in Texas. We also decompose the portions of transit projects to separately assess them in terms of access.

Questions

This chapter addresses the following questions:

- How does the service area variation affect the access-based evaluation of transit projects?
- What are the advantages of decomposing the access changes in access-based evaluation of transit projects?
- How do transit planners benefit from decomposing the access changes in access-based evaluation of transit projects?

Methods

Study area and project description

The following subsections provide information about the study area of the two projects (1) Metro Transit A Line in Minnesota and (2)

Harris County Transit Re-Imagined Bus Network in Texas, and their objectives in detail.

Project 1: Metro Transit A Line Metro Transit, the regional transit authority for the Minneapolis - St. Paul Area, performed a study, which concluded in 2012, to select local high ridership routes for service upgrades. The purpose of these upgrades was to provide a faster, higher quality service to existing riders and in the process potentially attract new riders. Several corridors emerged from the initial plan and they were broken down into a number of proposed projects. The first of these projects to be implemented is the Metro Transit A Line.

The Metro Transit A Line is a north-south route based on the local Route 84. Route 84 travels along Snelling Avenue and 46^{th} Avenue between the Rosedale Mall and the 46^{th} Street LRT Station on the Blue Line, with a connection to the Green Line at the Snelling Avenue Station. Metro Transit found that Route 84 buses, only spent approximately half of their running time in motion. The other half of the time was largely split between time spent at bus stops while passengers boarded and alighted and time spent waiting at lights. Only a small fraction of the total time not in motion was associated with traffic congestion.

In order to reduce delays and create a faster route the A Line project added off-board fare collection and raised curbs at stations to reduce boarding time per passenger, reduced the stop density from a stop approximately every 200m to a stop approximately every 800m, and worked with other agencies to get transit priority at signals. Note, the local Route 84 still stops approximately every 200m but also benefits from the transit signal priority and off-board fare collection at the stops it shares with the A Line.

The 20 stops made by the A Line were upgraded to include raised curbs, off-board fare collection, improved way finding features including ADA accessible route information, and shelters to provide a quality and welcoming experience for users. In addition, new buses were purchased for use on the A Line, with special high visibility branding to distinguish the Arterial Bus Rapid Transit (aBRT) service from other bus services, particularly as the aBRT network expands to include additional lines. Finally, with six trips per hour, the A Line runs at a higher frequency than the original Route 84, which had four trips per hour but with the implementation of the A Line only has two trips per hour.

Project 2: Harris County Transit Harris County Transit redeveloped their bus network from scratch. The historic existence of a bus route was not considered a reason to have a route there in the future, however existing infrastructure was taken into consideration. The reasoning for this approach to the bus network redevelopment came from five key factors:

- a decline in ridership in the region,
- the fast pace of changing development patterns in the Houston area,
- the opening of new light rail services freeing up former bus investments,
- public feedback for an improvement of the core bus network, and
- an assessment of the systems performance in comparison to past performance and peer performance.[15]

[15] (Pritchard 2015).

In place of historic existence, the redevelopment plan focuses on the provision of productive services.

The resulting Re-imagined Network provides five services: (1) a frequent network with headways of 15 minutes or less over a 15-hour period of the day with at least 3 hours of additional service at 20- or 30-minute headways on both weekend and weekdays, (2) a base network providing 30-minute headways for at least 18 hours a day on weekdays and weekends, (3) coverage service providing 60-minute headways and some 30-minute peak headways with a 14-hour span on both weekdays and weekends, (4) a peak only service that has high frequency in peak directions and low frequency in off-peak directions, and (5) a high expense flex service which is provided on demand and operates in predefined areas.[16] In addition, during the course of the planning for the Re-imagined Bus Network, two additional light rail lines were opened in the Houston area, which replaced existing bus services at a combined cost of approximately $1.4 billion. These lines were open to the public in May of 2015.

[16] (Pritchard 2015).

The analysis performed as part of this chapter will focus only on the first four services, or more plainly only on the fixed route services. This chapter, therefore, considers three scenarios:

- **Scenario A:** this is the baseline scenario, in which neither the light rail lines nor Re-imagined Bus Network have been implemented. It is represented by the Harris County Transit general transit feed specification (GTFS) of March 2015.

- **Scenario B:** this is the scenario in which the light rail lines have been implemented but the Re-imagined Bus Network has not. It is represented by the Harris County Transit general transit feed specification (GTFS) of May 2015.
- **Scenario C:** this is the full implementation scenario, in which both the light rail lines and Re-imagined Bus Network have been implemented. It is represented by the Harris County Transit general transit feed specification (GTFS) of November 2015.

Data

This chapter employs the cumulative opportunities measure[17] to calculate both access to jobs and access to workers. This method, by definition, determines the access level of a given origin location by the number of opportunities that can be reached within a given travel time threshold. For calculation, we use the travel time thresholds of 10, 20, 30, 40, 50, and 60 minutes. This enables us to evaluate the effects of analysis boundaries on access measurement in distinct time thresholds. For details of methodology, the reader is referred to the relevant references.[18]

[17] See chapter 1 in this volume.

[18] (Owen et al. 2015).

For the purpose of access-based evaluation of the projects, it is fundamental to recalculate transit access in different scenarios. This requires modifying the data and accommodating the effects of scheduling in calculation. We obtained the following data sets for the Metro Transit A Line and Harris County Transit Re-Imagined Bus Network projects:

- Project 1: The Metro Transit A Line project
  1. Baseline Network: Metro Transit General Transit Feed Specification (GTFS) release for November 2015.
  2. Metropolitan Council Transportation Analysis Zone (TAZ) shapefile and forecasts for population and employment in 2040 based on ThriveMSP.
  3. Planning documents that describe the changes to the Twin Cities Transit network and will be implemented as part of the A Line aBRT project. These descriptions were used to modify the existing GTFS files to reflect the proposed changes.
- Project 2: The Harris County Transit Re-Imagined Bus Network Project

1. Harris Transit GTFS Release for March 2015 for the analysis of Scenario A .
2. Harris Transit GTFS Release for May 2015 for the analysis of Scenario B.
3. Harris Transit GTFS Release for November 2015 for the analysis of Scenario C.
4. System Re-imagining Report. A document describing the proposed changes, which indicates that access calculations could have been performed as early as September 2014.

Buffer zone access

The Twin Cities Metropolitan Area and the Houston Metropolitan Area are the first service areas considered for access-based evaluation of the projects. However, it is of interest to reduce the project area in order to reduce the impact of areas which are not affected by the changes made to the transit network on the analysis. This helps understand how and to what extent the service area definition affects the performance of transit projects. We create six buffer zones concerning the distance that can be walked from the bus stops. We assume the typical worker can walk at a speed of 5 km/hr. Consequently, in a period of 30 minutes, a person would be able to walk up to 2,500m. The zones were generated for 10 minutes, 20 minutes, 30 minutes, 40 minutes, 50 minutes, and 60 minutes of available walk time, resulting in buffers zones of 833m, 1,667m, 2,500m, 3,333m, 4,167m, and 5,000m, respectively. Figure 18.1 and Figure 18.2 illustrate the buffer zones.

Project 1: Metro Transit A Line project Table 18.1 depicts access to jobs in the A Line and baseline scenarios for different number of minutes when using distinct service area definitions. The similar information for access to workers is depicted in Table 18.2. Comparing the A Line and baseline scenarios, it is found that adding the A Line significantly boosts both worker-weighted and job-weighted access, apart from the service area definition. Due to the limited size of the project, limiting the service area helps improve the understanding of how the project impacts access. In particular, both worker-weighted and job-weighted access increase when a smaller service area is taken into consideration, and so do the percent differences between these in the A Line network as

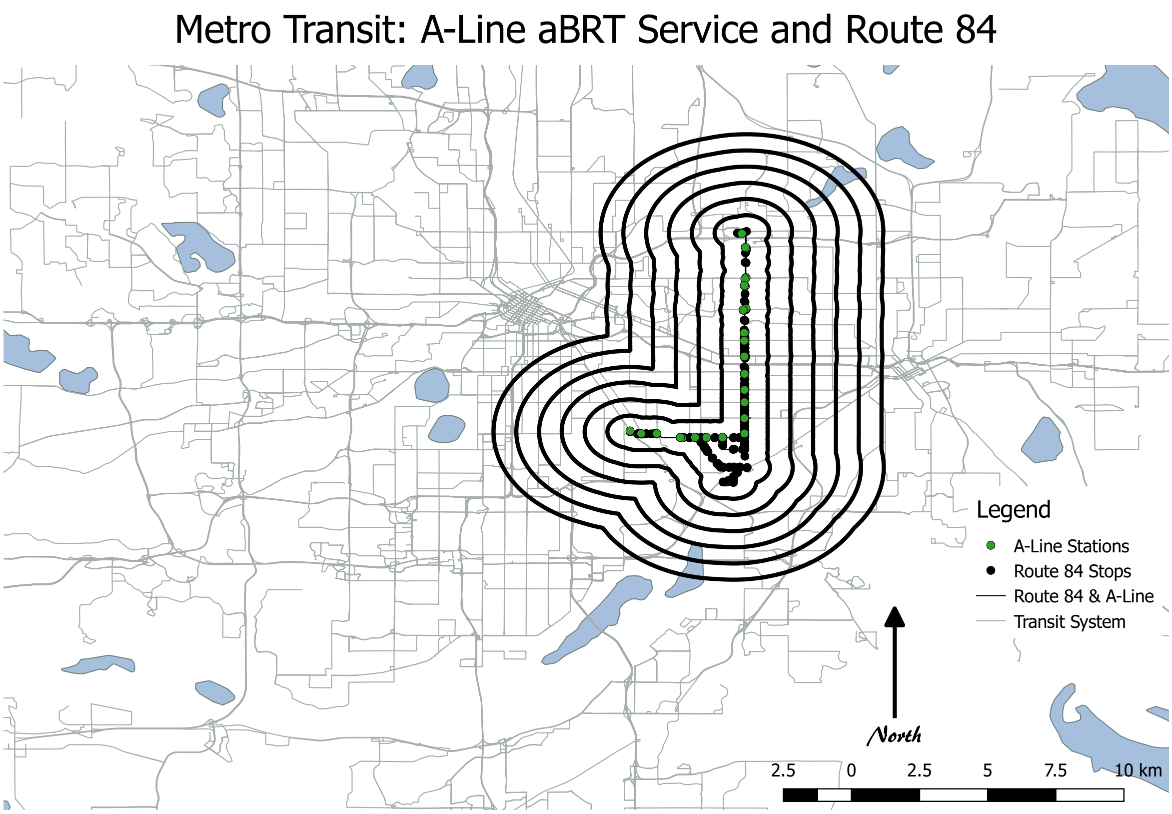


Figure 18.1: All six buffer zones utilized in the access calculations for the A Line analysis are represented in this map, they surround the A Line and Route 84, showing the status of both bus stops and routes

compared to the baseline network. This is demonstrated by comparing the access values in different service areas.

Looking at Table 18.1 and Table 18.2, it is inferred that a reduction in service area not only increases both worker-weighted and job-weighted absolute access values, but it also escalates the percentage changes in access. For example, workers living within 2,500m of the A Line can reach 5.92% more jobs within 30 minutes with the new service than before, which is about 2,500 additional jobs within 30 minutes. Employers in that same area can reach 5.41% more workers, or nearly 1,400 more potential employees. However, workers living within 833m of the A Line can reach 10.87% more jobs within 30 minutes with the new service than before, which equals 4,682 additional jobs within 30 minutes.

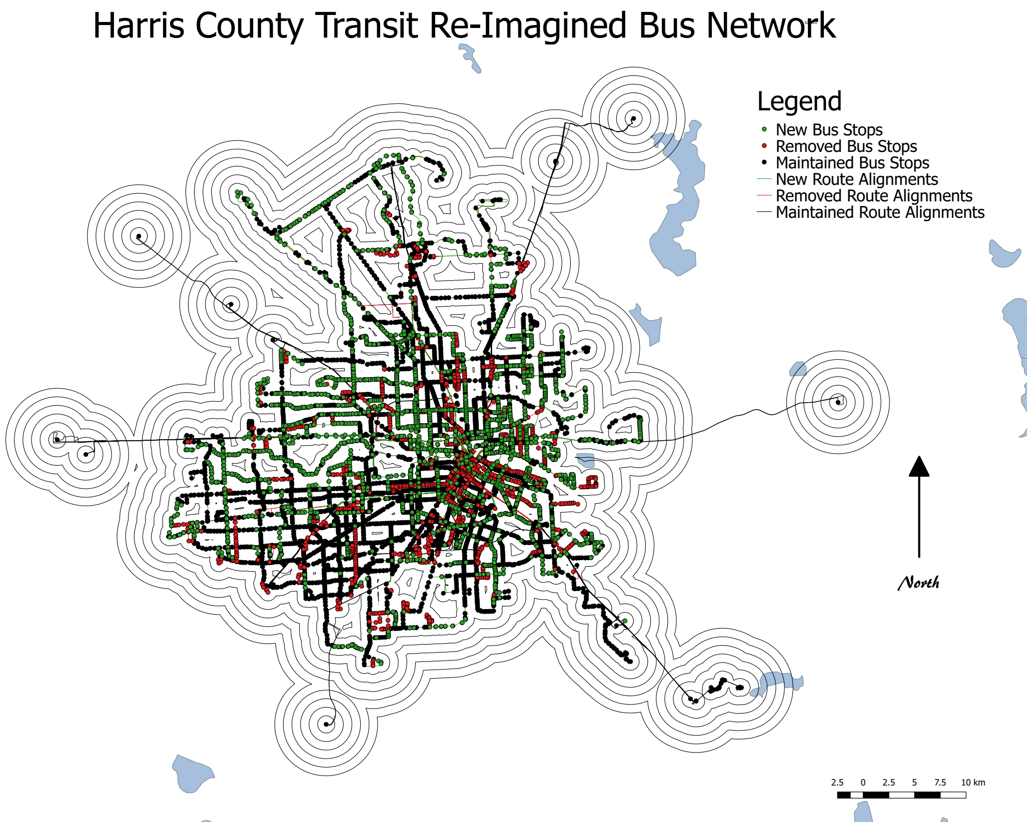


Figure 18.2: All six buffer zones utilized in the access calculations for the Harris County Transit analysis are represented in this map, they surround the Harris County Transit System, showing the status of both bus stops and routes

Employers in that same area can reach 6.39% more workers, or 2,029 more potential employees.

Project 2: Harris County Transit Re-Imagined Bus Network At the Houston Metropolitan service area level, Figure 18.3 illustrates the percent change in the number of jobs that can be reached from each block, averaged between 7:00 AM and 9:00 AM. Likewise, Figure 18.4 represents the percent change in the number of workers that can be reached from each block, averaged between 7:00 AM and 9:00 AM.

Akin to the results of Project 1, the access values vary significantly from zero to hundreds of thousands across all blocks. We speculate that this variation is a direct result of the transit service history in the

Table 18.1: Access to jobs for Metro Transit A Line using different service area definition

Minutes	Service Area (Meters)						
	Metro	5,000	4,167	3,333	2,500	1,667	833
Baseline Scenario							
10	597	1062	903	910	937	1,059	1,135
20	4,885	9,513	8,600	8,063	7,943	8,421	8,845
30	19,296	49,925	46,058	44,414	42,058	42,428	43,072
40	47,278	151,511	148,891	148,932	145,554	147,068	147,458
50	88,310	293,361	297,148	304,504	308,283	319,608	329,788
60	139,629	439,576	445,869	455,990	462,475	479,364	496,727
A Line Scenario							
10	597	1061	902	909	935	1,056	1,131
20	4,898	9,661	8,786	8,292	8,237	8,824	9,439
30	19,428	51,277	47,706	46,410	44,547	45,732	47,754
40	47,786	156,332	154,714	155,954	154,391	158,745	163,963
50	89,238	302,283	307,760	317,082	323,777	339,218	355,824
60	140,805	448,869	456,490	467,875	476,169	494,958	513,845
Absolute Changes in Access							
10	0	-1	-1	-1	-2	-3	-4
20	13	148	186	229	294	403	594
30	132	1,352	1,648	1,996	2,489	3,304	4,682
40	508	4,821	5,823	7,022	8,837	11,677	16,505
50	928	8,922	10,612	12,578	15,494	19,610	26,036
60	1,176	9,293	10,621	11,885	13,694	15,594	17,118
Percentage Changes in Access							
10	0.00	-0.09	-0.11	-0.11	-0.21	-0.28	-0.35
20	0.27	1.56	2.16	2.84	3.70	4.79	6.72
30	0.68	2.71	3.58	4.49	5.92	7.79	10.87
40	1.07	3.18	3.91	4.71	6.07	7.94	11.19
50	1.05	3.04	3.57	4.13	5.03	6.14	7.89
60	0.84	2.11	2.38	2.61	2.96	3.25	3.45

Minutes	Service Area (Meters)						
	Metro	5,000	4,167	3,333	2,500	1,667	833
Baseline Scenario							
10	625	750	752	764	772	805	911
20	4,889	6,270	5,821	6,007	6,217	6,647	7,630
30	19,738	25,115	23,479	24,327	25,485	27,451	31,767
40	51,057	63,895	60,955	63,122	65,528	69,890	78,258
50	97,711	123,009	119,879	124,256	127,815	135,089	145,480
60	155,676	199,658	198,276	206,693	212,100	222,743	233,898
A Line Scenario							
10	625	749	752	763	771	804	909
20	4,908	6,352	5,938	6,151	6,397	6,859	7,941
30	19,911	25,871	24,468	25,506	26,864	28,985	33,796
40	51,691	66,142	63,766	66,379	69,239	73,903	83,155
50	98,945	126,971	124,865	130,025	134,315	141,858	152,557
60	157,118	204,989	204,985	214,405	220,622	231,233	241,900
Absolute Changes in Access							
10	0	-1	0	-1	-1	-1	-2
20	19	82	117	144	180	212	311
30	173	756	989	1,179	1,379	1,534	2,029
40	634	2,247	2,811	3,257	3,711	4,013	4,897
50	1,234	3,962	4,986	5,769	6,500	6,769	7,077
60	1,442	5,331	6,709	7,712	8,522	8,490	8,002
Percentage Changes in Access							
10	0.00	-0.13	0.00	-0.13	-0.13	-0.12	-0.22
20	0.39	1.31	2.01	2.40	2.90	3.19	4.08
30	0.88	3.01	4.21	4.85	5.41	5.59	6.39
40	1.24	3.52	4.61	5.16	5.66	5.74	6.26
50	1.26	3.22	4.16	4.64	5.09	5.01	4.86
60	0.93	2.67	3.38	3.73	4.02	3.81	3.42

Table 18.2: Access to workers calculation for Metro Transit A Line using different service area definition

region, as adding transit service to a region with little or no service produces a high percentage change in access values.

Table 18.3 depicts access to jobs in the Re-imagined Bus Network and baseline scenarios for a different number of minutes when using distinct service area definitions. Table 18.2 summarizes the similar information of access to jobs for access to workers. Looking at Table 18.3 and Table 18.4, it is found that an increase in both worker-weighted and job-weighted access follows a decrease in the service area. This is not significant when considering the percentage change in access dissimilar to Project 1. For instance, workers living within 2,500m of the Re-imagined Bus Network can reach 475 additional jobs within 30 minutes with the new service, while this number equals 611 for the 833m service area. This indicates workers who reside closer to the system generally have higher access to jobs. The percentage change in access, however, is fairly similar. This is also true for job-weighted access. Employers living within 2,500m of the Re-imagined Bus Network can reach 159 more jobs within 30 minutes with the new service, while employers living within 833m of the Re-imagined Bus Network can reach 180 additional jobs within 30 minutes. The percentage change in access, however, equals around 0.90% for both situations.

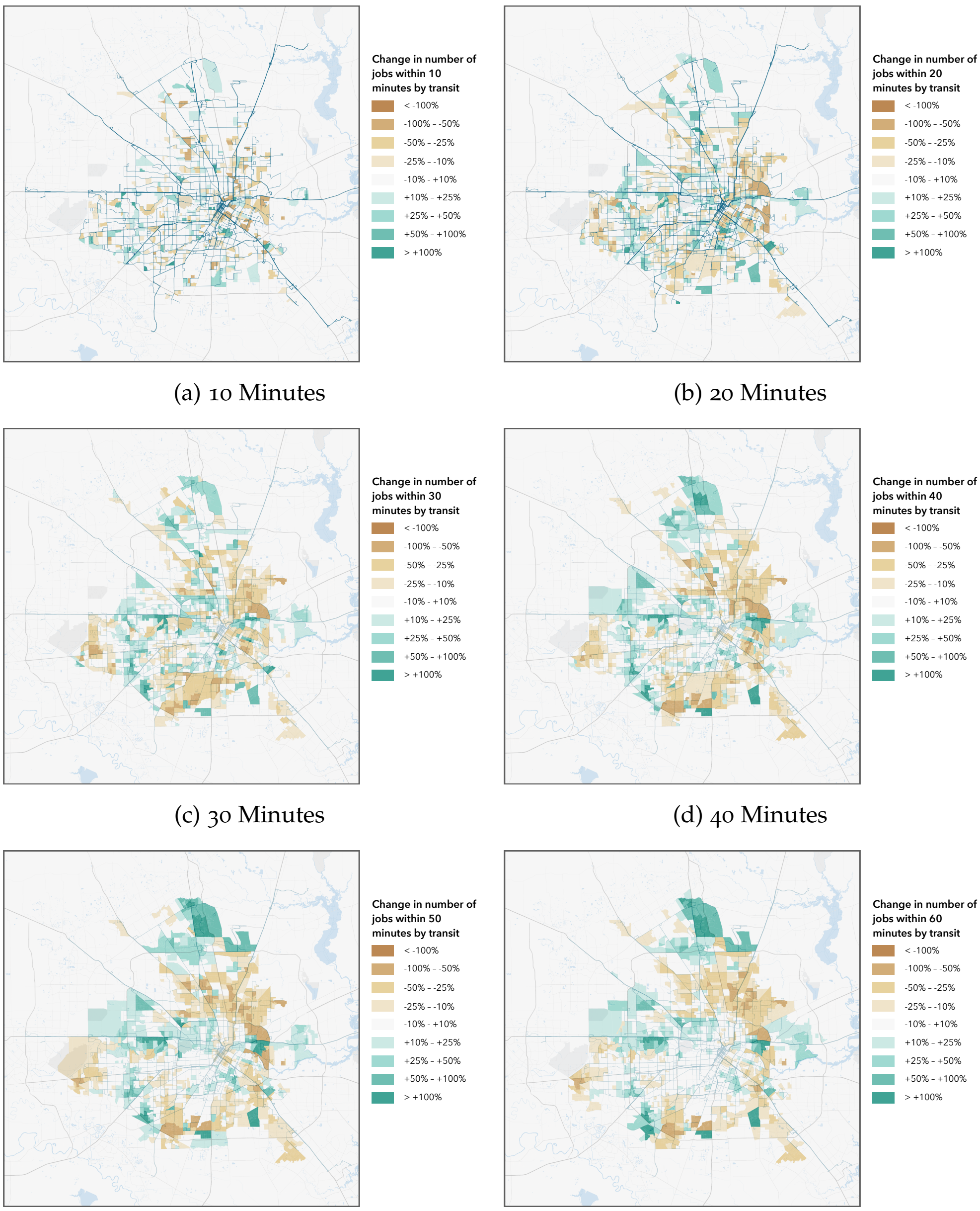
If comparisons were made between regional areas, the selection of analysis area in each region could have a large impact on the results, simply by virtue of the size of the region relative to the size of the network. For Project 2, the percentage change in access in an exact service area is similar to the percentage change in access in another service area. However, this is not the case for Project 1.

Findings

In this section, we aim to determine how and to what extent the separate portions of transit projects impact access-based evaluation. The following subsections provide an in-depth discussion over the two selected transit projects.

Project 1: Metro Transit A Line

We calculate and compare access to jobs and access to workers in different time thresholds at the Minneapolis - St. Paul metropolitan region level for four different scenarios:



(a) 10 Minutes

(b) 20 Minutes

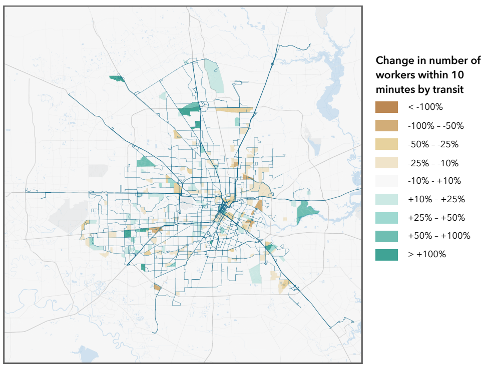
(c) 30 Minutes

(d) 40 Minutes

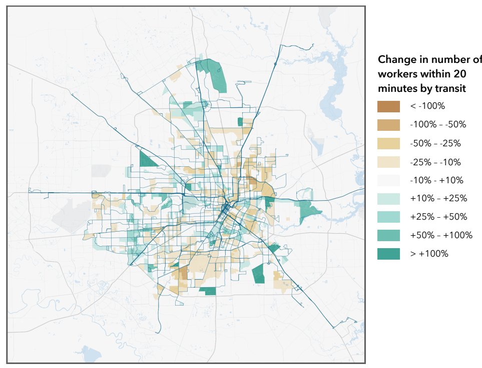
(e) 50 Minutes

(f) 60 Minutes

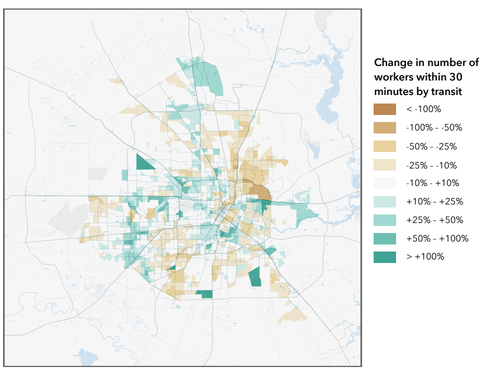
Figure 18.3: Change in number of total jobs reachable by threshold (Scenario C vs. Scenario A and 2013 land use)



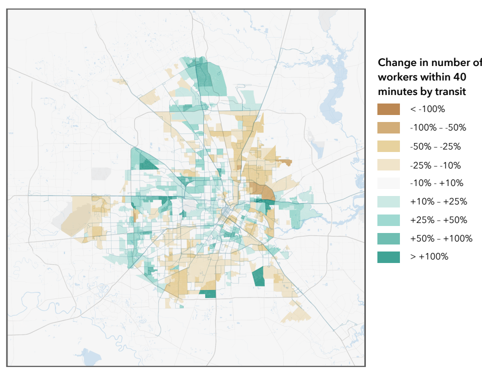
(a) 10 Minutes



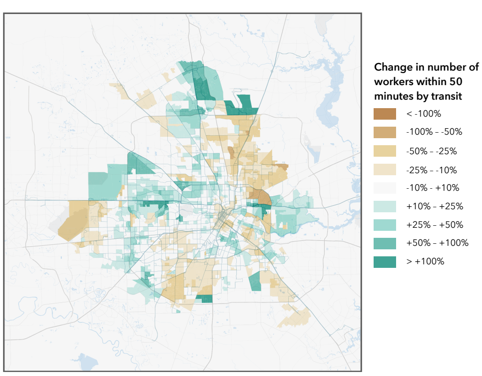
(b) 20 Minutes



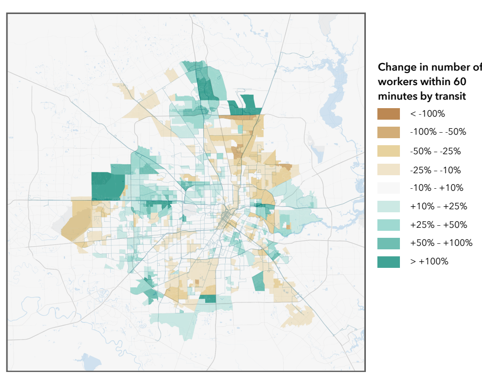
(c) 30 Minutes



(d) 40 Minutes



(e) 50 Minutes



(f) 60 Minutes

Figure 18.4: Change in number of total workers reachable by threshold (Scenario C vs. Scenario A and 2013 land use)

Minutes	Service Area (Meters)						
	Metro	5,000	4,167	3,333	2,500	1,667	833
Baseline Scenario							
10	496	724	771	823	900	983	1,101
20	3,616	5,588	5,979	6,467	7,124	7,883	8,896
30	13,044	20,852	22,353	24,272	26,831	29,805	33,655
40	32,034	51,950	55,745	60,604	67,156	74,735	84,463
50	63,027	103,206	110,824	120,556	133,729	148,955	168,381
60	107,330	177,443	190,652	207,513	230,308	256,644	289,798
Re-Imagined Bus Network Scenario							
10	485	705	750	801	875	955	1,069
20	3,651	5,629	6,023	6,515	7,178	7,944	8,966
30	13,275	21,212	22,741	24,697	27,306	30,338	34,266
40	32,296	52,321	56,146	61,042	67,644	75,284	85,096
50	63,326	103,821	111,488	121,282	134,540	149,866	169,443
60	107,996	179,164	192,509	209,544	232,577	259,189	292,793
Absolute Changes in Access							
10	-11	-19	-21	-22	-25	-28	-32
20	35	41	44	48	54	61	70
30	231	360	388	425	475	533	611
40	262	371	401	438	488	549	633
50	299	615	664	726	811	911	1,062
60	666	1,721	1,857	2,031	2,269	2,545	2,995
Percentage Changes in Access							
10	-2.22	-2.62	-2.72	-2.67	-2.78	-2.85	-2.91
20	0.97	0.73	0.74	0.74	0.76	0.77	0.79
30	1.77	1.73	1.74	1.75	1.77	1.79	1.82
40	0.82	0.71	0.72	0.72	0.73	0.73	0.75
50	0.47	0.60	0.60	0.60	0.61	0.61	0.63
60	0.62	0.97	0.97	0.98	0.99	0.99	1.03

Table 18.3: Access to jobs for Harris County Transit using different service area definition

Table 18.4: Access to workers for Harris County Transit using different service area definition

Minutes	Service Area (Meters)						
	Metro	5,000	4,167	3,333	2,500	1,667	833
Baseline Scenario							
10	492	579	588	595	611	631	661
20	3,577	4,441	4,538	4,662	4,807	5,023	5,314
30	12,800	16,370	16,764	17,302	17,886	18,737	19,890
40	31,317	40,518	41,542	42,955	44,480	46,702	49,655
50	61,564	80,458	82,540	85,434	88,564	93,151	99,056
60	104,903	138,494	142,140	147,233	152,733	160,826	170,928
Re-Imagined Bus Network Scenario							
10	482	566	576	582	597	616	645
20	3,581	4,458	4,556	4,681	4,827	5,044	5,336
30	12,856	16,511	16,911	17,454	18,045	18,905	20,070
40	31,242	40,747	41,778	43,200	44,737	46,974	49,940
50	61,253	80,779	82,870	85,778	88,922	93,529	99,441
60	104,462	139,030	142,692	147,808	153,332	161,450	171,549
Absolute Changes in Access							
10	-10	-13	-12	-13	-14	-15	-16
20	4	17	18	19	20	21	22
30	56	141	147	152	159	168	180
40	-75	229	236	245	257	272	285
50	-311	321	330	344	358	378	385
60	-441	536	552	575	599	624	621
Percentage Changes in Access							
10	-2.03	-2.25	-2.04	-2.18	-2.29	-2.38	-2.42
20	0.11	0.38	0.40	0.41	0.42	0.42	0.41
30	0.44	0.86	0.88	0.88	0.89	0.90	0.90
40	-0.24	0.57	0.57	0.57	0.58	0.58	0.57
50	-0.51	0.40	0.40	0.40	0.40	0.41	0.39
60	-0.42	0.39	0.39	0.39	0.39	0.39	0.36

Table 18.5: Decomposing access changes for Metro Transit A Line

Minutes	Scenario A	Scenario B	Scenario C	Scenario D
Regional Worker-Weighted Access to Jobs				
10	597	596	599	597
20	4,885	4,848	4,920	4,898
30	19,296	19,058	19,513	19,428
40	47,278	46,565	47,950	47,786
50	88,310	87,079	89,464	89,238
60	139,629	138,301	141,048	140,805
Regional Job-Weighted Access to Workers				
10	625	624	625	625
20	4,889	4,857	4,927	4,908
30	19,738	19,515	19,992	19,911
40	51,057	50,387	51,860	51,691
50	97,711	96,469	99,216	98,945
60	155,676	154,221	157,634	157,118

- **Scenario A:** this is the baseline scenario with the local service (Route 84 bus).
- **Scenario B:** this is the scenario in which we cut the local service.
- **Scenario C:** this is the scenario with adding the A Line to the network without removing the local service.
- **Scenario D:** this is the full implementation scenario, in which the the local service is removed and the A Line is added to the network.

We present the results in Table 18.5. Comparing Scenario A with Scenario B, we observe a decrease in access, but the opposite is true comparing Scenario A with Scenario C. Scenario D falls in between the Scenario B and Scenario C, as expected, but is generally greater than the baseline network access.

Project 2: Harris County Transit Re-Imagined Bus Network

We calculate and compare access to jobs and access to workers in different time thresholds at the Houston metropolitan region level for three different scenarios:

- **Scenario A:** this is the baseline scenario, in which neither the light rail lines nor Re-imagined Bus Network have been implemented.
- **Scenario B:** this is the scenario in which the light rail lines have been implemented but the Re-imagined Bus Network has not.

Table 18.6: Decomposing access changes for Harris County Transit

Minutes	Scenario A	Scenario B	Scenario C
Regional Worker-Weighted Access to Jobs			
10	496	493	485
20	3,616	3,609	3,651
30	13,044	13,047	13,275
40	32,034	31,998	32,296
50	63,027	62,945	63,326
60	107,330	107,131	107,996
Regional Job-Weighted Access to Workers			
10	492	491	482
20	3,557	3,574	3,581
30	12,800	12,807	12,856
40	31,317	31,292	31,242
50	61,564	61,484	61,253
60	104,903	104,768	104,462

- **Scenario C:** this is the full implementation scenario, in which both the light rail lines and Re-imagined Bus Network have been implemented.

We outline the results in Table 18.6. Comparing the scenarios in the regional worker-weighted access to jobs, the light rail implementation in Scenario B had a nearly negligible, though generally negative, impact on access to jobs in comparison to Scenario A. This is reasonable, as the light rail lines that replaced the bus service also changed the stop locations. In contrast, the restructuring the network in addition to the investment in light rail (Scenario C), had a small but generally positive impact on the ability of users to reach jobs in comparison to both Scenario A and B. This indicates that the re-allocation of resources inherent in the Re-imagined Bus Network produced a positive impact without the need for a significant investment. Due to the generally negative though negligible impacts of Scenario B in comparison to Scenario A, it is clear that the inclusion of the light rail investment in Scenario C actually provides for a slight underestimation of the effects of the Re-imagined Bus Network to the baseline network. Together these observations support the conclusion that the implementation of the Re-imagined Bus Network has a small but positive impact on the access to jobs in the region.

The analysis of the access changes for the Harris County Transit with the implementation of their new light rail system and the restructuring of the bus network indicated that the light rail investments had negligible impacts on access levels while the restructuring of the bus network had slight positive impact on

access to jobs. The evaluation of the impact of access to jobs and workers with the implementation of these projects for users within various buffer zones of the transit network provided interesting results. In general, workers residing closer to the transit network, understandably had higher levels of access. However, the buffer zone chosen to perform the analysis did not impact the relative levels of the results between scenarios. This is to say that whether access was evaluated at a regional level or within an 833m buffer zone of the transit network, Scenario C showed a consistent percent increase in access to jobs over Scenario A. These results support the idea that comparisons across different regions can be problematic without a consistent definition of areas to be included in an analysis.

Conclusions

The analytical issues associated with the modifiable areal unit problem are neither unfamiliar nor peculiar in the transport planning realm. Many examples of the modifiable areal unit problem and its potential consequences exist in transport literature and in real-world applications.[19] The topic, however, has been given little attention particularly by planners and transit officials when evaluating transit projects. The recent emergence of the use of access-based evaluation in transport projects has renewed some interest in the MAUP, resulting in research focusing on developing scale-free access measurements or exploring the appropriate unit of analysis to measure access. Scant empirical evidence exists to evaluate the service area variation impacts of the access measure in transit projects.

[19] (Biehl et al. 2018).

This empirical research describes an extensive analysis of the sensitivity of the access-based evaluation results to variations in the definition of transit service areas. In particular, we examined the role of transit service area definition in access-based evaluation in two distinct transit projects: (1) Metro Transit A Line in Minnesota and (2) Harris County Transit Re-Imagined Bus Network in Texas. The results indicated that choice of transit service areas have a significant impact on the value of absolute access measures. In general, the trend showed that the narrower the analysis boundary is to the network, the higher the value of the absolute access measure. The results were inconsistent when relative access measures such as percentage change between scenarios is used as

an access-based evaluation measure. This demonstrates that service area definition is of only moderate importance for scenario comparisons within the same analysis boundary. When comparing between different regions or in areas within different boundaries, the service area definition could have a significant impact on all results. This is case sensitive and varies greatly from project to project, which necessitates calculating both the absolute and relative access measures in access-based evaluation.

In addition, evaluating the Harris County Transit Project helped examine the role of bus service development in providing regional access. The results revealed that the light rail investments had negligible impacts on access levels while the restructuring of the bus network had slight positive impact on access to jobs. The conclusion, of course, has a regional evaluation benefits and are not generalizable to other transit projects. However, we recommend decomposing transit projects in access-based evaluation to pick the right choice.

Next

The findings of the current research have important implications for the deployment of access-based evaluation on transit projects. Testing the impacts of service area definitions in access-based evaluation avoids pitfalls resulting in contradictory or illusory conclusions. The findings and recommendations of the current research must be considered in light of the limitations. We examined service area variation impacts of the access measure in two distinct transit projects, and focused only on cumulative opportunities access calculations. Although we feel that the findings indicate the need for researchers to conduct similar access-based evaluation for transit projects, we assert that further research is needed to substantiate our findings.

19
Access-based Evaluation of Transit - Oriented Developments

Chelsey Palmateer, Andrew Owen, and Alireza Ermagun

Abstract: This chapter uses the access-based evaluation method to unpack the interaction effect of transit-oriented development and a new transit hub, using the San Francisco Transbay Transit Center Development Plan project. We reveal both the transit-oriented development and transit changes positively affect access to jobs and access to workers. However, the magnitude of effects for the transit changes alone are minimal in comparison to the effects of the anticipated transit-oriented development changes. This indicates that in areas where there already is transit service, the development of land near the transit service can have a greater impact on access levels than the improvement of connections between transit services. We also unravel the increase in access at the project-level and determine that the increase is greater than the sum of the contributions of the individual portions of the project. This demonstrates that transit changes and transit-oriented development can have a superadditive effect, although it is negligible in our case.

Introduction

Transit-oriented development (TOD) has become the focus of advocates and planners who are interested in creating multi-use facilities around transit hubs.[1] TOD-based design fosters benefits for communities that reach across the spectrum. For individuals, this "smart-growth" allows them to live in closer proximity or have a better access to their valued destinations, and become less dependent on an automobile for transport. For transit agencies,

Keywords: Transit-oriented development; Access; Transit project evaluation; San Francisco

[1] (Cervero and Duncan 2002).

planners, and advocates, TODs have the potential of solving problems of housing shortages, pollution, and traffic congestion.[2] Transit ridership, promoting economic development and job growth, raising revenues for transit properties, enhancing livability, and widening housing choices rank as the top five goals for the transit-oriented development.[3]

[2] (Sung and Oh 2011).

[3] (Cao and Ermagun 2016, Cervero 2004).

Access analysis bifurcates two categories in which TODs are evaluated. The first category is regional analysis over time, which analyzes the benefits of a project on the region over time. A regional analysis over time measured the access of the Minneapolis-St. Paul region by automobile by examining TAZ data from 1995 to 2005.[4] The second category is regional scenario analysis over space, which looks at the impact of a regional project in one region versus the impact of a project in a different region. In 2010, this method was employed to evaluate the access of transit among different socio-economic groups in Detroit for non-work trips.[5]

[4] (Levinson et al. 2017).

[5] (Grengs et al. 2010).

Transit projects involving the implementation or renovation of a hub for multiple transit services also incorporate plans for transit-oriented development. Planners and advocates are then interested in evaluating the interaction effects, in addition to gauging the benefits of transport investment and land development independently.

The interaction effect then takes on one of the following three forms:

- First, the effect is superadditive, if the joint benefits surpass the sum of the benefits, which are gained from development and transport investment.
- Second, the effect is subadditive, if the joint benefits reduce the sum of the benefits.
- Third, the effect is additive, if the joint benefits equal the sum of the benefits.[6]

[6] (Kanchi et al. 2002).

Although the existing body of literature on assessing transit projects supports the need for an access-based evaluation on different portions of a transit project as a package,[7] the research in this area remains in its infancy. This chapter uses the access-based evaluation method to unpack the interaction effect of both transit-oriented development and constructing a new transit hub in San Francisco, California.

[7] See chapter 18 in this volume.

Questions

This chapter addresses the following question:

- Are public transport network investments and transit-oriented developments superadditive, subadditive, or additive?

The answer to this questions help planners and advocates understand whether and to what extent the transit projects in access terms benefit from both the transport investment and the land development.

Methods

Project design implementation

The San Francisco Transbay Transit Center Development includes two main project components:

- The construction of the new Transbay Transit Center and Transit Tower to replace the existing Transbay Terminal as well as the relocation of transit services to the new Transbay Transit Center and extension of Caltrain from Fourth and King St. Station to the Transbay Transit Center.

- Transit-oriented development both within the Transit Center District and in the nearby Rincon Hill neighborhood.

The Transbay Transit Center and adjacent Transit Tower are shown in yellow in Figure 19.1. The Transbay Transit Center replaces the previous Transbay Terminal (the temporary location of the Transbay Terminal is shown as a blue dot at the corner of Folsom St. and Main St.). However, the new Transbay Transit Center is multimodal and incorporates a planned extension of Caltrain from the Fourth and King St. Station (shown as a green dot). Eventually the future California High-Speed Rail may also connect to the Transbay Transit Center.

The Transit Center will include a rooftop park and require a reconfiguration of local streets to accommodate anticipated changes in traffic patterns, such as increased pedestrian traffic. In addition, the Transit (Salesforce) Tower, at a height of 326m, is adjacent to the Transbay Transit Center. The Transit Tower includes three floors of below-grade parking, four floors of retail space, and office space on

the remaining floors. In terms of access, the primary impact of the relocation of the transit services to the combined center will be an enhanced connection between various transit services.[8]

[8] (Department 2008).

The Transit Center District and Rincon Hill Plans complement the new transit infrastructure. Figure 19.1 shows the boundary of the Transit Center District Plan with a dotted red line. The plan is for both private property and property owned by the Transbay Joint Powers Authority. As of 2008, the area was about 40 acres containing the temporary Transbay Terminal and access ramps and various vacant and underutilized properties. Many of the buildings within the project area are aging and in a state of deterioration, or simply do not meet modern construction standards.

New development within the Transit Center District includes office space and residences, primarily focused in Transbay Zone 2. To accommodate the taller building of the new development, the City of San Francisco plans for updated height restrictions in Zone 2. Efforts in Transbay Zone 1 will largely be focused on streetscaping, with little land use or height changes. In Figure 19.1, Transbay Zone 1 and Transbay Zone 2 are shown with light purple and green shading, respectively.[9] In the nearby Rincon Hill neighborhood there is another plan encouraging high-density residential uses, with funding mechanisms to incorporate affordable housing and other public infrastructure.

[9] (Department 2008).

Between these two planning efforts, a growth of approximately 21,500 jobs and 2,700 residential units in Transbay Zone 1 and Zone 2 combined as well as 3,822 residential units in the Rincon Hill neighborhood is anticipated. The project is defined by the combination Transbay Zone 1, Transbay Zone 2, and the Rincon Hill neighborhood; however the access impacts are assessed at the regional level.

Access measurement and calculation

The cumulative opportunities measure[10] is used for multiple threshold times in Access Across America.[11] In addition, several techniques allowing for comparison of access by transit across systems are utilized. The first is the introduction of time averaged access to account for the variability in access associated with transit scheduling. This methodology requires the measurement of access on a minute by minute basis during the period of interest.[12] Second is the use of person-weighted access in order to aggregate the access

[10] See chapter 1 in this volume.

[11] (Owen and Levinson 2014).

[12] (Owen and Levinson 2014).

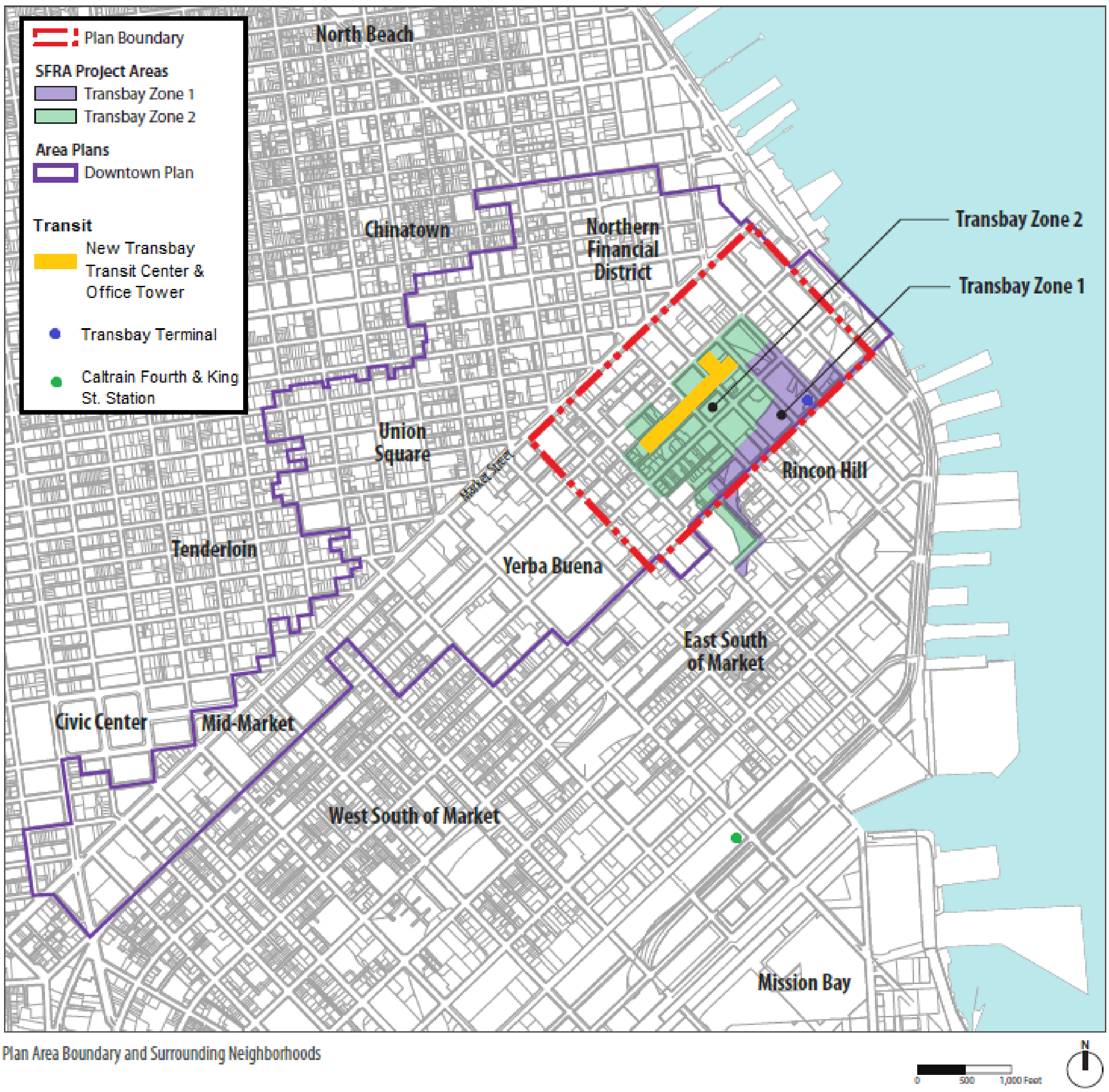


Figure 19.1: Transit Center District Plan and Transit Tower. Source: (Department 2008)

measurements at the census block level to a region. The access is averaged over all census blocks with each block's access weighted by the population of workers in the census block. Finally, to provide an overall ranking, which takes into account the access at each of the measured thresholds, a weighted access is determined as in Equation Equation 19.1.[13]

[13] (Owen and Levinson 2014).

$$a_w = \sum_T (a_T - a_{T-10}) e^{\beta T} \tag{19.1}$$

Where:
a_w = Weighted access ranking metric for a single metropolitan area
a_T = Worker-weighted access for threshold t
β = -0.08

Data preparation and modification

For the purpose of access-based evaluation analysis, we use six particular data sets as follows:

1. US Census TIGER 2010 data sets: blocks, core-based statistical areas (CBSAs).

2. US Census Longitudinal Employer-Household Dynamics (LEHD) 2013 Origin-Destination Employment Statistics (LODES).

3. OpenStreetMap (OSM) North America extract, retrieved in January 2016.

4. Planning documents which describe the anticipated growth in residential units. The documents encompass jobs and include: the Transit Center District Plan Draft of November 2009, the Notice of Preparation of EIR: Transit Center District Plan and Transit Tower of July 2008, and the San Francisco General Plan for Rincon Hill Area Plan.

5. Baseline Transit Network, which includes the San Francisco Municipal Transportation Agency (SMFTA) GTFS release for November 2015 and the Caltrain GTFS release for November 2015.

6. Three travel surveys consist of San Francisco Bay Area Travel Survey 2000, which mentioned in the project planning documents, the 2013 California Household Travel Survey, and the

Census Transportation Planning Products – 2000 Workers per Household provided by USDOT.

In the following subsections, we provide an in-depth discussion over the data preparation and modification.

GTFS modification

To generate General Transit Feed Specification (GTFS) for the network after the Transbay Transit Center is complete, the baseline GTFS network needed to be modified according to the proposals made in the planning documents. GTFS requires a minimum of six text files to sufficiently describe a transit network. These files include: `agency.txt`, `stops.txt`, `routes.txt`, `trips.txt`, `stop_times.txt`, and `calendar.txt`. GTFS also allows for the addition of numerous optional text files to provide additional information. Five of these files are affected by the modifications to the network and a brief description of each follows:

- `stops.txt` lists all stops in the transit network, providing a unique ID as well as latitude and longitude of each stop base on the WGS 84 datum. New stops are added to this file as part of the modifications.

- `routes.txt` lists all routes in the network, providing a unique ID for each route, as well as a short name and other basic information. New routes are added to the file as part of the modifications.

- `trip.txt` lists all trips in the network providing a unique trip ID, the associated route ID, and other basic information about the trips. New trips are added to this file, and the data for rescheduled trips is changed to reflect the modifications.

- `stop_times.txt` contains the scheduling information. This file lists the time that each trip is at an associated stop, as well as the associated trip ID and stop ID. Whether a trip is rescheduled or completely new, all the stops in the trip and the times at those stops are added to this file as part of the modifications (old stop times for rescheduled trips are deleted). However, in some cases a single trip can be used as a representative for many trips. In that case, the stop times are only included once, and the frequency of the trip is indicated in the frequencies.txt file.

- `frequencies.txt` includes the desired headway of the trip, as well as information about the duration of that headway, and the ID of the associated trip.

As part of the modifications for the Transbay Transit Center implementation, it was necessary to define the alignment for all trips that would terminate at the new Transbay Transit Center. As such, the former terminals of these routes were adjusted to reflect their new location at the Transbay Transit Center, by simply changing the stop location. It was assumed that travel times would remain the same for all routes.

Land use estimates

The *Transit Center District Plan Draft* describes the growth of approximately 21,500 jobs and 2,700 residential units in Transbay Zone 1 and Zone 2 combined. The *San Francisco General Plan: Rincon Hill Area Plan* further describes growth of approximately 3,822 residential units in the Rincon Hill neighborhood. It is necessary to make an assumption about the number of workers per household to determine the expected growth in number of workers based on assumed growth in the number of residential units. We utilized the San Francisco Bay Area Travel Survey 2000, which is mentioned in the project planning documents, to generate an estimate of 1.18 workers per household. This rate is reasonable in comparison to both the estimate of 1.22 workers per household at the national level as provided by the USDOT Census Transportation Planning Products and the estimate of 1.31 workers per household from the 2013 California Household Travel Survey. Due to its local relevance and mention in the planning documents, 1.18 workers per household seems to be the most useful estimate for this analysis.

Land use modifications

In the San Francisco Transbay Development the primary change of concern is the development of land. To represent an implementation of the development proposed in these projects, changes are made to the baseline Longitudinal Employer-Household Dynamics (LEHD) data from each case study. The US Census Longitudinal Employer-Household Dynamics 2013 Origin-Destination Employment Statistics (LODES) consists of three files. The first is a file of origins and destinations of commutes to work, which is not

used as part of this analysis. The second is a file containing workplace area characteristics (WAC). This file details the number of jobs by category in each census block. The third file contains residential area characteristics (RAC). This file details the number of workers by category that live in each census block.

In case studies with anticipated development, the planning documents are reviewed to determine the geographic extents of the project and anticipated growth in residential units and commercial space. The anticipated growth in total workers can then be estimated by multiplying the typical number of workers per household by the anticipated number of new residential units. Similarly, the anticipated growth in jobs is determined as the multiplication of the commercial usage factor, which is the number of workers per floor area of commercial space, by the anticipated increase in commercial floor area. In the case of the San Francisco Transbay development, this was not necessary because the planning documents indicated an anticipated growth in the number of jobs rather than an anticipated growth in commercial square feet. The total increase in workers and jobs for the projects are then distributed to all potential census blocks within the projects based on the percentage of the total project area within each census block. For example, a census block that has twenty percent of the total land area of the project will receive twenty percent of the projected growth in jobs and workers. These increases are added to the baseline total number of workers in the RAC file and total number of jobs in the WAC file to generate digitized representations of the proposed land use. Finally, it is assumed that the relative ratio of total jobs to any category of jobs (e.g., jobs with earnings $1250/month or less) and the relative ratio of total workers to any given category of workers (e.g., race of workers) remain constant so that the predictions for these categories of jobs and workers can be populated based on the predicted total jobs and total workers.

Findings

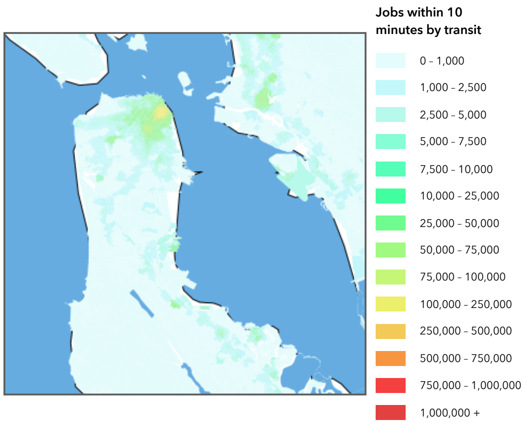
The San Francisco Transbay Transit Center Development access to jobs and access to workers calculations were performed, and the access to jobs and access to workers results were processed. The maps in Figure 19.2 illustrate the access by transit to jobs, averaged between 7:00 AM and 9:00 AM, in the baseline scenario. The maps in Figure 19.3 illustrate the change in the number of jobs and

workers respectively that can be reached from each block based on the development of the Transbay Transit Center. When interpreting these maps, it is important to note that they show percentage, rather than absolute, access changes. Across all blocks in the region the range of access values is wide: from some blocks no jobs can be reached by transit, while from others, hundreds of thousands of jobs can be reached. When a transit service is added to an area that previously had little or no service, the low original access value can produce a very high percentage change, even if the absolute number of new jobs that can be reached is relatively low. This can also result in anomalous blocks if an area having very low access experiences slightly more or less walking distance due to rounding in the access calculation program.

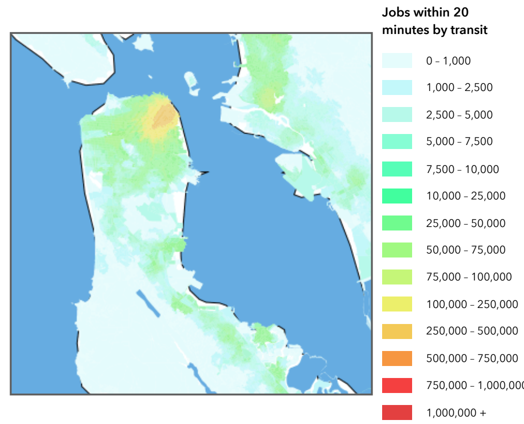
Figure 19.3 shows that the development of the Transbay Transit Center and Rincon Hill results in increases in access to jobs. In addition, it is interesting to note that there is a high percentage change in access to workers, who are localized within or near the project area, for thresholds at or below 30 minutes, with little or no change in higher thresholds. This localization is likely due to the already high levels of access experienced by areas surrounding the project. A similar phenomenon occurs for access to jobs, however at higher thresholds the areas impacted are further from the project area. This is likely due to the larger growth in jobs than workers coupled with the lower access to jobs in the areas showing higher percent increases than in the areas near the project at thresholds at or above 40 minutes, as demonstrated in Figure 19.2. Table 19.1 further illustrates that the San Francisco Bay Area as a whole experiences increases in access to both jobs and workers respectively at all thresholds due to the development directly, with an additional benefit of a lower magnitude associated with the relocation of transit services to the Transbay Transit Center and thereby closer to the planned development.

To give the reader a quantitative sense of how the access is changed following the San Francisco Transbay Transit Center redevelopment plan, we outline the weighted access to jobs and workers in Table 19.1 for different scenarios.

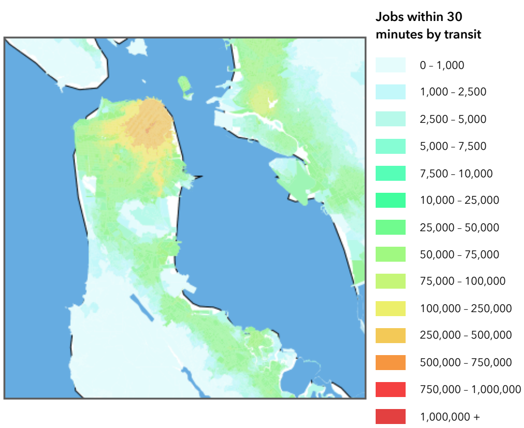
Both the TOD and the transit changes impact access levels. However, the impacts of the transit changes alone are minimal in comparison to the effects of the anticipated TOD changes. For example, given only the land use changes the typical worker can reach an additional 1,647 jobs in 30 minutes. However, given only



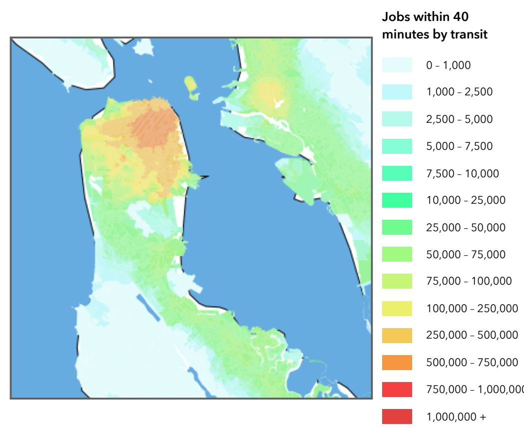
(a) 10-minute threshold.



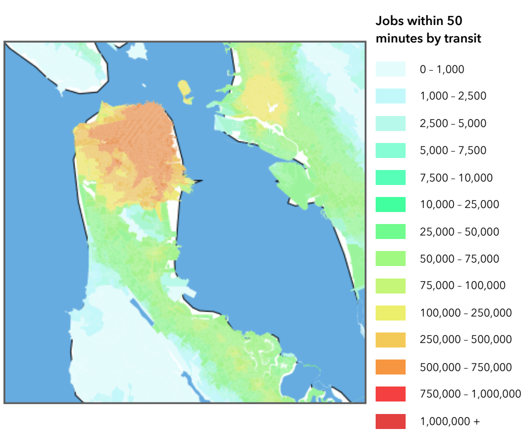
(b) 20-minute threshold.



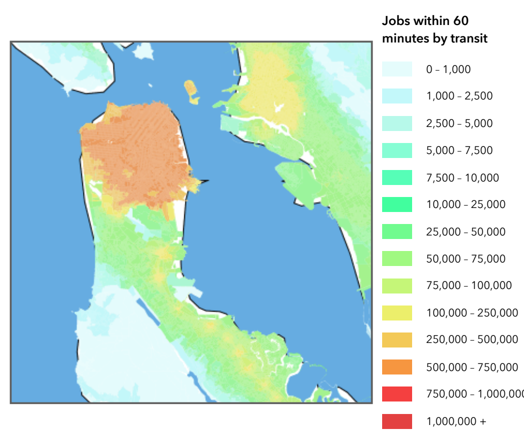
(c) 30-minute threshold.



(d) 40-minute threshold.

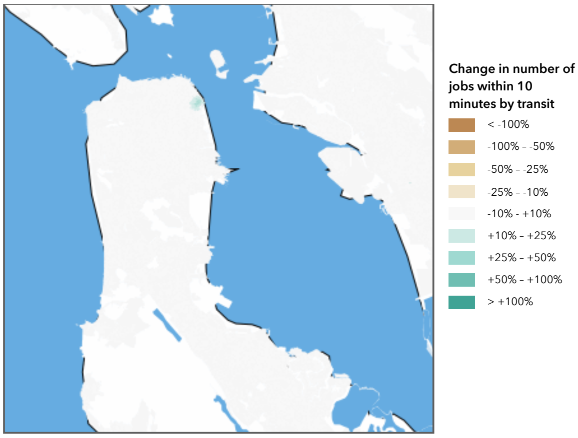


(e) 50-minute threshold.



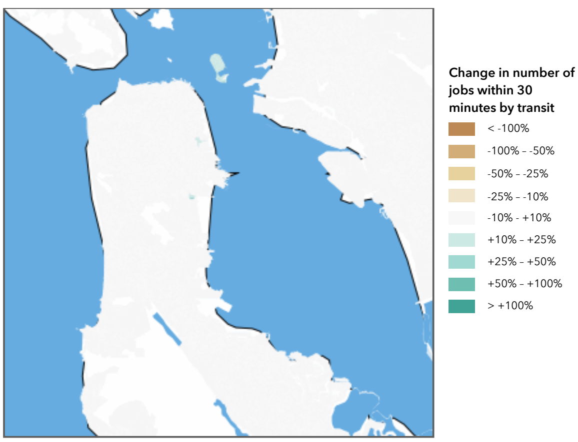
(f) 60-minute threshold.

Figure 19.2: Total jobs reachable by threshold (Baseline network and 2013 land use)

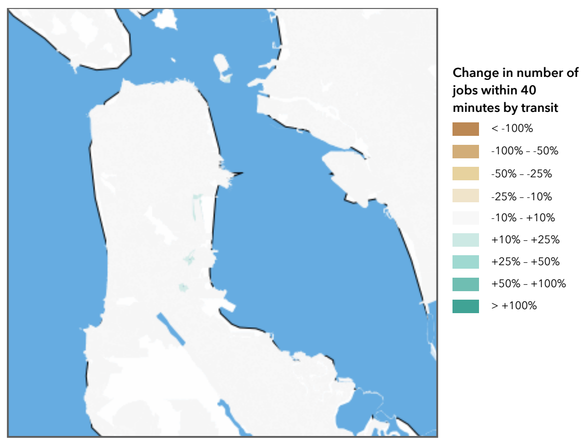


(a) 10-minute threshold.

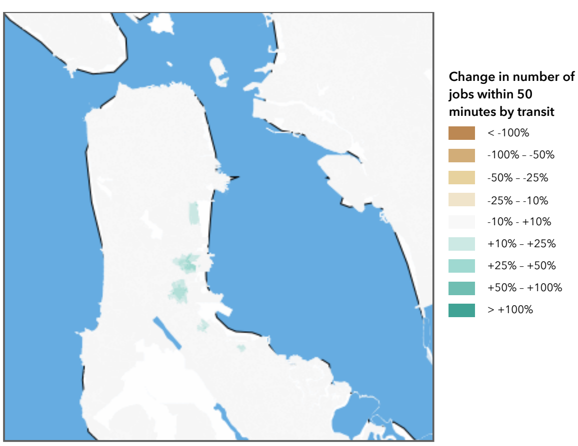
(b) 20-minute threshold.



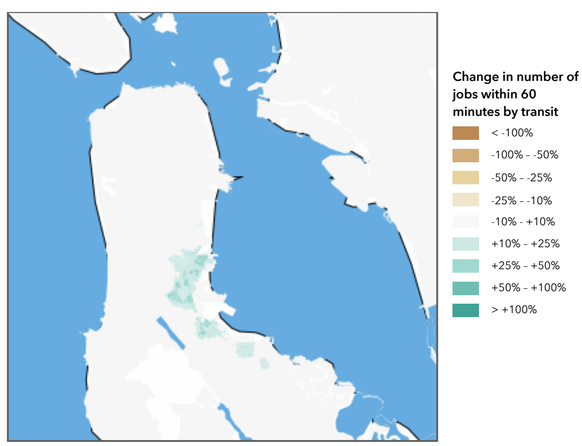
(c) 30-minute threshold.



(d) 40-minute threshold.



(e) 50-minute threshold.



(f) 60-minute threshold.

Figure 19.3: Change in number of total jobs reachable by threshold

Scenarios	Number of Minutes					
	10	20	30	40	50	60
			Access to Jobs			
Access Calculation						
2013 LEHD	1,500	10,290	28,248	52,674	78,602	100,995
TOD	1,698	11,156	29,895	55,161	81,828	104,748
Transit	1,500	10,291	28,253	52,688	78,638	101,124
TOD and Transit	1,699	11,156	29,903	55,181	81,880	104,917
Access Changes						
TOD	198	866	1,647	2,487	3,226	3,753
Transit	0	1	5	14	36	129
TOD + Transit	198	867	1,652	2,501	3,262	3,882
TOD and Transit	199	867	1,655	2,507	3,278	3,922
Interaction Effects	Superadditive	Superadditive	Superadditive	Superadditive	Superadditive	Superadditive
			Access to Workers			
2013 LEHD	1,460	10,167	27,088	49,319	73,491	95,216
TOD	1,642	10,977	28,597	51,485	76,250	98,390
Transit	1,617	10,169	27,105	49,379	73,595	95,422
TOD and Transit	1,642	10,978	28,618	51,555	76,374	98,639
Access Changes						
TOD	182	810	1,509	2,166	2,759	3,174
Transit	157	2	17	60	104	206
TOD + Transit	339	812	1,526	2,226	2,863	3,380
TOD and Transit	182	811	1,530	2,236	2,883	3,423
Interaction Effects	Subadditive	Subadditive	Superadditive	Superadditive	Superadditive	Superadditive

Table 19.1: Weighted access to jobs

the transit changes the typical worker can reach an additional 5 jobs in the same time threshold. When the two changes are both taken into account, the typical worker can reach only an additional 1,655 jobs. This is more than the sum of the benefits of the individual projects, which is 1,652 additional jobs. This demonstrates that transit projects and TOD can have a superadditive effect. A similar pattern is observed for the increase in the access to workers.

The impacts of the transit changes alone are less than the effects of the anticipated TOD changes. Considering only the new land changes, the additional regional workers that a typical company can reach within 30 minutes of travel is 1,509 workers. This value equals 17, in the only transit change scenario. When the two changes are both taken into account, the typical company can reach an additional 1,530 workers. This is slightly more than the sum of the benefits of the individual projects, which is 1,526 additional jobs. Unlike the access to jobs that is superadditive in all minutes of

travel, the access to workers is superadditive in greater than 20 minutes of travel. Although we show that transit projects and transit-oriented development can have a superadditive effect on transit access, the effects of transit-oriented development may be far greater than the effects of transit changes. This is especially true in the case where transit changes are made in an area with pre-existing service.

Conclusions

We evaluated the interaction effect of transit-oriented development and transit hubs in the Transbay Transit Center Project underway in San Francisco, California. Enhancing the access to jobs and workers is a promising regional economic benefit of the Transbay Transit Center Project. For companies, the widening talent pool should expand productivity. For workers, particularly low-income households, access to affordable transport is the biggest impediment to employment. Many low-income households do not have easy access to public transit and thereby increase the time spent on their commute to and from work. The Transit Center, and by extension the downtown rail, is not only tasked with creating better access to affordable transit to all of San Francisco, but to focus explicitly on residents in the poorer southern neighborhoods and the Peninsula corridor. We encapsulate the key remarks of the access-based evaluation in the following annotations:

- The transit-oriented development has a significant impact on enhancing access to workers. The number of regional workers that a could be reached from typical job within 30 minutes of travel, between 7:00 AM and 9:00 AM using transit, increases by about 5.5%. Akin to access to regional workers, the transit-oriented development has a significant impact on enhancing access to jobs. The number of regional jobs that a typical worker residing in the region can reach within 30 minutes of travel, between 7:00 AM and 9:00 AM using transit, increases by 6.0%.

- Although transit hubs enhance access to jobs and workers, the impact is negligible. The number of regional jobs and workers that a typical worker residing in the region can reach within 30 minutes of travel, between 7:00 AM and 9:00 AM using transit, increases by less than one percent.

- The interaction effect analysis revealed that the joint access benefit of the transit-oriented development and creating transit hubs, generally in this case, exceed the sum of the accesses, which gain from each development independently. This pinpoints that transit-oriented development and transit hubs can have a superadditive effect. While, this effect is minimal in this case, we speculate that the slight interaction effect drives from the fact that the area is already benefiting from a decent transit service.

Next

Planners and transit officials might use the findings of the current research to properly invest in transit projects. Evaluation of transit projects at the project-level aligns the planning strategies with expectations, which increases the effectiveness of investments. Planners also can use access-based evaluation used in this chapter to detect project quality weaknesses and strengths. This leads them to allocate corporate resources to the important parts of the project and properly fulfill their targets.

20

Physical and Virtual Access

Tanhua Jin, Long Cheng, and Frank Witlox

Abstract: This chapter presents a comprehensive review of how virtual access interacts with physical access and how the interaction affects travel-access relationships. Information and communication technology (ICT), access, and travel behavior have been integrated both in theoretical and empirical studies. ICT enables people to access goods, services, and opportunities in cyberspace without spatial-temporal travel resistance. Access can then be divided into virtual and physical access, which refers to the opportunities to reach teleactivities and location-based counterparts, respectively. Existing studies regarding the impacts of virtual access on physical activities can be categorized into questions about substitution, complementary, modification, fragmentation, and multitasking. Teleactivities, like online shopping, distance learning, and telework, can substitute for face-to-face contacts or trigger more physical activities, which are reshaping travel-access relationships. Travel demand, frequency, time, and distances may change since people's travel patterns are influenced by the interactions between virtual and physical accessibility.

Introduction

Keywords: Virtual access; Physical access; Travel behavior; ICT; Travel-access relationships

Following the emergence of Information and Communications Technology (ICT), the concept of twin activities emerged, indicating that in person activities typically have virtual twins.[1] Access is traditionally defined as "the extent to which land-use and transport systems enable individuals to reach activities or destinations by different modes of travel."[2] This geospatial definition may no longer be appropriate as virtual access is emerging as a potential alternative to physical access. As ICT permeates daily life, the

[1] (Hjorthol and Gripsrud 2009).

[2] (Cheng et al. 2019; 2020, Geurs and Van Wee 2004).

boundary between virtual and physical worlds begins to blur. Physical and virtual access usually refer to the ease with which certain activities can be reached in the physical space and in cyberspace, respectively. Virtual access eases reaching to destinations without taking a trip and might improve travel experiences benefiting from real-time information using ICT.

Virtual access has dramatically changed lifestyles, habits, quality of life, and health status. It has improved work efficiency and productivity by virtually connecting people without physical constraints. People can respond to their needs from home, which has contributed to the quality of life of people with disabilities and the elderly.

The importance of virtual access becomes more clear under emergency conditions such as extreme weather and public health hazards.[3] Due to the threat of COVID-19, people are restricted by stay-at-home orders and have fewer opportunities to conduct their physical activities than usual.[4] Most people are encouraged to interact with the world through virtual access since social distancing has become a new norm to help slow down the spread of the virus.[5] Total travel frequency is thus dropping as more people work from home. Students are increasingly interacting with learning materials and teachers via distance learning. Compared with on-campus study, online courses provide students with more flexible temporal and spatial management of their studies. People may also change their travel mode and choose not to take public transit to avoid contact with the crowd. They may drive and walk more than before.

The dramatic revolution of ICT devices has profoundly reshaped the relationship between virtual access and travel behavior. ICT applications were once based on communicating using landlines (e.g., teleworking or teleshopping from home),[6] while wider use of high-tech devices like virtual reality (VR), augmented reality (AR), and autonomous vehicles (AV) would allow people to perform virtual activities with fewer spatial and temporal constraints. Research focusing on a specific virtual activity and its effect on the travel demand to the on-site counterparts was the dominant research interest from the early 1990s till 2010s, leading to a "substitution" vs "complementary" debate. Since the development of smartphones, virtual access no longer merely refers to getting access to physical activities at home via computers with a landline Internet connection, but using ICT anywhere and anytime, which

[3] (Abdullah et al. 2020).

[4] (Shamshiripour et al. 2020).

[5] (van Wee and Witlox 2021).

[6] (Cohen-Blankshtain and Rotem-Mindali 2013).

results in new concepts like modification, multitasking, and fragmentation. In addition, researchers have gradually acknowledged that aggregate level conclusions become less explanatory, and heterogeneity analysis at the individual level can help further the understanding of the effect of virtual access on travel behavior. This chapter reviews how virtual access interacts with physical access and how the interaction affects travel-access relationships to provide a better sense of future directions in this space.

Questions

This chapter addresses the following questions:

- Substitution or complementary debate: does virtual access reduce or generate travel demand?

  Whether virtual activities can serve as substitutes for physical counterparts or stimulate physical travel has engendered controversy since the term "telecommuting" was introduced.[7] concluded that telecommunication devices have various effects on multiple activities: substitution effect on work-related activities, complementary effect on recreation activities.

- Modification, fragmentation, or multitasking: how does virtual access influence travel patterns?

  Relationships between virtual and physical access do not simply refer to the conclusion of "more" or "fewer" trips. Considering the connection between choice, location, mode, and duration of activities and travel is more profound than focusing only on specific aspects of such relationships. ICT may affect travel behavior directly by changing travel patterns, leading to a further debate about modification, fragmentation, and multitasking effects. The modification effect has a secondary effect on travel patterns, by changing trip frequency, destination, mode, and route of travel.[8] The fragmentation effect enables a certain activity to be divided into several pieces and be performed at different times and/or locations,[9] while multitasking means that people can conduct multiple activities simultaneously.

- How heterogeneous are the impacts of virtual access on travel behavior?

[7] (Ren and Kwan 2009).

[8] (Cohen-Blankshtain and Rotem-Mindali 2013).

[9] (Hubers et al. 2008).

Even though the average is vital, variation in different groups still matters, allowing for a further understanding of the effect of virtual access on travel. Different effects may be found, depending on the category of activity, gender, and age of respondents, the extent to which people adopt virtual activity, and other personal characteristics.[10]

[10] (Pan et al. 2009, van Deursen and van Dijk 2013).

Methods

This section reviews methods that are commonly used to address the questions noted above.

Regression models and Structural Equation Models (SEM) are two of the most widely used methods to examine how ICT influences travel behavior. Regression models such as linear, logistic, Poisson, negative binomial regression models, concentrate more on the direct effects of independent variables on dependent variables. When using such regression models, indicators of ICT are independent variables, while indicators of travel behavior are dependent variables.[11] However, the interactions between virtual access and travel behavior are much more multifaceted and complicated. The causal relationship between ICT and travel behavior may be bidirectional. For example, telecommuting may result in a longer commute distance, while a longer commute distance may also encourage telecommuting adoption. Some researchers concluded that simple single-equation models like regression models may be insufficient to demonstrate a thorough understanding of relationships in related studies. Sophisticated models, like SEM, path analysis, factor analysis, have then been applied to travel behavior-related analysis. For example, besides capturing associations between exogenous variables (virtual access) and endogenous variables (travel behavior), SEM is also able to quantify the causal interactions between independent variables. In summary, SEM can estimate direct, indirect, and total effects, which helps gain a better understanding of the complex interactions between ICT and travel behavior.[12]

[11] (Shi et al. 2019; 2021).

[12] (Ben-Elia et al. 2018).

Quasi-longitudinal analysis, hierarchical clustering algorithm, and multiple discriminant analysis are also employed to examine how ICT affects travel behavior. The quasi-longitudinal analysis can be used to examine the before and after effect of ICT usage on travel behavior.[13] A hierarchical clustering algorithm is used to cluster the preferences for types of destinations for users with different levels

[13] (Shi et al. 2019).

of internet usage intensity.[14] Multiple discriminant analysis is applied to examine the variations across representative patterns in terms of ICT usage, personal and household attributes.[15]

[14] (Wang et al. 2018).

[15] (Alexander et al. 2010).

To conclude, multiple methods have been applied to understand the interactions between virtual accessibility and travel behavior. However, machine learning methods are barely discussed in existing research. Machine learning methods have the advantage of examining complex relationships, such as nonlinear and threshold effects. For example, random forest, gradient boosting decision trees, and support vector machines have become promising methods in the recent field of travel behavior studies.[16]

[16] (Koushik et al. 2020).

Findings

Substitution

Location-based activities may be replaced by their virtual counterparts, like e-shopping, distance education, online work, and cyber-medicine, leading to an elimination of travel. Some researchers concluded substitution took place, indicating that telecommuting may lead to a reduction of Vehicle Miles Traveled (VMT).[17]

[17] (Cheng et al. 2020, Choo and Mokhtarian 2007, Mokhtarian 1991).

Three-day panel diaries collected from the California Pilot Commuting Project to measure respondents' travel characteristics of pre- and post-telecommuting indicate that telecommuting caused a 20% reduction in total travel and 75% of total distance traveled.[18] Eight telecommuting programs showed a reduction on average 36.1 person miles traveled and 26.2 VMT for work-related trips for telecommuters.[19]

[18] (Pendyala et al. 1991).

[19] (Mokhtarian et al. 1995).

With virtual access to information about goods, people may decrease unnecessary travel to physical stores to seek and find the exact goods they need. Respondents avoided 20% of shopping trips for every 100 minutes they spend on teleshopping using the San Francisco Bay Area Travel Survey 2000.[20] A sample of 3200 Internet users in the Netherlands, found that teleshoppers are more likely to take less time for shopping travel, take fewer shopping trips, and travel shorter total distance.[21] In models of Chengdu, more than 44% of the respondents decreased shopping trip frequency due to teleshopping, and only 14.9% show the opposite.[22]

[20] (Ferrell 2005).

[21] (Hiselius et al. 2015).

[22] (Shi et al. 2019).

People can be immersed in a virtual environment via VR technologies without being in the real world in person, thus they

may reduce their travel frequency. AR combines real and virtual objects to create a real-time view of a physical environment by overlaying virtual information. Customers can try on clothes and cosmetics from high-tech systems like 'Magic Mirror'.[23] They do not need to travel to different malls to find the exact and perfect products they need. AR devices, along with the game, also can enhance people's senses by allowing them to smell, touch, hear like they would in the real world. Using AR interfaces, gaming apps can be regarded as substitutes for doing exercises outside.[24] These high-tech gadgets are now changing people's travel preferences and reducing their travel frequency by making home-based activities as appealing as outdoor activities.

[23] (Rashid et al. 2017).

[24] (Schlomann et al. 2020).

This substitution effect may be extended to the concept of substitutability. Substitutability is 'the extent to which preferred travel alternatives can be substituted by other initially less preferred alternatives' in the context of travel behavior.[25] For example, Dynamic Route Information Panels may enable people to switch to public transport mode to avoid ongoing traffic jams. Virtual access can also offer substitutability of goods, services, and even contacts since people are more likely to achieve this substitutability by gaining sufficient information via ICT devices. Substitutable goods or services have a positive cross-elasticity of demand.

[25] (van Wee et al. 2019).

Smartphones and the Internet are "monitoring" people's lives with algorithms analyzing the behaviors of phone use and online activities. It may be more likely for us to find information on substitute products or services since Internet trackers retain search histories and provide discounts or deals based on their preference algorithms.

Complementary

Though policymakers claimed that telecommuting would have a positive effect on reducing traffic congestion, air pollution, and urban problems from the 1980s to the early 1990s, the reality was contrary to expectations.[26] Thus, some other scholars raised questions like the following, "if telecommunication is such a good substitute for travel, why does congestion continue to get worse?"[27] which triggered research on complementary. Virtual access to opportunities can not only reduce spatio-temporal travel resistance but also increase individuals' efficiency of engaging in location-based activities.

[26] (Pérez Pérez et al. 2004).

[27] (Mokhtarian 2013).

Many scholars conclude that ICT may have a complementary effect on physical shopping activities, rather than be a substitute for travel,[28] concluding that teleshopping does not reduce travel demand and perhaps even triggers more shopping trips. Similarly, in the context of Dutch studies, researchers observed that teleshoppers are more willing to buy at offline stores.[29] Sample data derived from a travel characteristics survey in Hong Kong to examine the relationship between ICT and travel behavior found that ICT generated additional out-of-home recreation activities and increased trip-making propensity.[30]

[28] (Casas et al. 2001, Kim et al. 2015, Mokhtarian and Salomon 2002, Zhu 2011).

[29] (Farag et al. 2006; 2007; 2006).

[30] (Vyas et al. 2019).

With the widespread development of China's e-commerce, a growing number of studies from China also confirmed similar findings.[31] Online searching positively affects both store and online shopping.[32] The wide adoption of virtual activities may not be a solution but a challenge to travel reduction. When people browse web pages, they may probably find that many advertisements are exactly the goods they want to buy. Such Internet marketing technology will recommend based on the items searched and thus stimulate consumer desire to have a shopping trip.[33]

[31] (Ding and Lu 2015, Zhen et al. 2016;?).

[32] (Xi et al. 2018).

[33] (Wang et al. 2018).

Autonomous vehicles (AVs) will, in principle, operate without a human driver. AVs will significantly reduce people's travel costs, and stimulate additional travel demand, especially for disadvantaged groups. Overall annual vehicle travel by the US population aged 19 and above would increase by approximately 14%, assuming non-drivers, elderly and people with travel-restrictive medical conditions will travel as often as the drivers within respective age group and gender.[34] Females would account for most of the increase, with the elderly seeing the greatest increase in VMT. Travelers may benefit from multiple travel choices as AVs can combine with transit and non-motorized travel modes more flexibly. Most joint travel will be eliminated and drivers (such as parents who drive their children every day) may have time for conducting other activities.[35]

[34] (Harper et al. 2016).

[35] (Vyas et al. 2019).

Modification

Travel patterns have also been changed by virtual access. As seen with COVID-19, telecommuting can change people's daily physical commute, such as shifting the time of travel from peak to off-peak times, or within the peak.[36] Teleshopping may simply modify trip patterns, for example, people may reduce their shopping trip

[36] (Gao and Levinson 2021).

frequency but increase their trip distance.[37] ICT devices may make longer-distance travel less appealing and people are more willing to get alternative virtual access to specific activities. They can relax people's spatio-temporal constraints and affect their ways of participating in activities.[38] Characteristics of certain trips, such as duration, distance, modes, and chaining may all be influenced by the interaction between virtual and physical access.[39]

37 (Mans et al. 2012).

38 (Schwanen and Kwan 2008).

39 (Mans et al. 2012).

A significant amount of spontaneous changes in activities and trips among 400 respondents in Chennai, India due to increased virtual access.[40] Millennials in the US tend to decrease their trip frequency and drive less, partially due to their more adoption of and frequent access to virtual activities.[41] Analysis of the 2014-2015 Puget Sound Regional Travel Study found that virtual access has made people become more likely to use multiple transport modes and complex trip chains with many intermediate stops and engage in trips containing leisure activities.[42] Based on the detailed individual data of 14- to 24-year-old from the project U.Move 2.0 in Germany, those who use ICT a lot also have more trips than those who do not.[43] Virtual access also increases the distance traveled and results in much longer motorized trips.

40 (Srinivasan and Raghavender 2006).

41 (McDonald 2015).

42 (Astroza et al. 2017).

43 (Konrad and Wittowsky 2018).

Virtual access to dynamic traffic information and online ticket systems may decrease the uncertainty of people's activity and trips, especially with the help of mobile phones. Such intelligent transport systems have also influenced people's mode choices and travel habits. Due to better information about different transport modes, people can easily change their trips and activities, alter their travel behavior and improve their travel experiences benefiting from interactive mapping, and intelligent route planning.

Fragmentation

It is possible that people can participate in a certain activity in a regular time sequence mixed with other activities, or at several different locations. The concept of fragmentation refers to "a process whereby a certain activity is divided into several smaller pieces, which are performed at different times and/or locations."[44] Travel can take place between different or new locations.

44 (Couclelis 2003).

The fragmentation of daily activities has followed on increased use of mobile phones and the Internet.[45] A framework to measure the fragmentation of work-related activities considering both time and space corroborates that the greater mobile phones and Internet

45 (Lenz and Nobis 2007)

people use, the more work activities fragmented temporally and spatially.[46] Work-related trips may decrease due to fragmentation while people may spend more time for non-work travel to conduct recreation activities.[47] In contrast, others have found no direct relationship between virtual access and temporal fragmentation, analyzing four types of activities, including work, daily shopping, non-daily shopping, and recreation activities.[48]

[46] (Alexander et al. 2010).

[47] (Ben-Elia et al. 2018).

[48] (Hubers et al. 2008).

Spatial and temporal fragmentation may have different effects on travel patterns. Mobile ICTs are more related to spatial fragmentation while landline ICTs contribute more significantly to temporal fragmentation.[49] The effects of fragmentation on work trips seem to be more temporal rather than being spatial. Greater temporal fragmentation reduces the frequency of work-related trips, and spatial fragmentation may make people more willing to choose to work at locations with greater travel distances since people are allowed to conduct their work across different locations.[50]

[49] (Alexander et al. 2010, Line et al. 2011).

[50] (Ben-Elia et al. 2018).

Multitasking

ICT has profoundly modified social relationships of being proximate and face-to-face. Cyber place provides us with Internet infrastructures and cables while cyberspace can be seen as mirrored world of physical space.[51] Products, information, and even people can have their digital counterparts in cyberspace. Distance and time can then be ignored. Co-presence was introduced as "a sense of being together in the virtual place where individuals become accessible, available and subject to each other."[52]

[51] (Devriendt et al. 2008).

[52] (Urry 2004).

People may be present in different digital spaces simultaneously and be able to deliver a sense of emotional closeness and have the feeling of being there. Such a phenomenon that people can easily conduct more than one activity at the same time is called "multitasking."[53] Travel can be seen as a primary activity and other activities can incidentally occur during travel. Travel-based multitasking using ICT devices can influence travelers' experience and satisfaction in various ways. People can simultaneously conduct multiple virtual activities during their trips, including talking on the phone, e-mailing their business partners, chatting with friends, social networking and dealing with works. Multitasking is making trips more enjoyable and travel time may be valued less negatively.[54] With the rapid development of 5G technologies, stable and fast connection speed can be accessed not

[53] (Circella et al. 2012).

[54] (Ettema and Verschuren 2007).

only from home but also during trips, making travel-based multitasking more efficient. However, drivers are not encouraged to actively use ICT devices to deal with multiple tasks during their trips, varying effects.[55]

[55] (McEvoy et al. 2007).

Heterogeneity

Existing literature indicates generational differences in virtual access. "Digital natives," often from the "millennials" and post-millennial generations, grew up with ICTs.[56] They hold more positive attitudes towards ICT use and have more virtual access than other generations. People from different regions may contribute to various conclusions due to cultural differences and the level of adopting ICT devices. For example, online shopping is extremely developed and popularized in China.[57]

[56] (Prensky 2001).

[57] (Zhen et al. 2016).

Light, moderate, and intense ICT users, who differ in their extent of use, are demographically different.[58] Those who use ICT intensely usually live in cities with lower access to private vehicles while light users come from lower-income households in rural areas. The intensive users are usually well-educated young people while the light users are more likely to be less-educated seniors. Intense users are apt to use multiple modes including transit and carsharing, while moderate and light users tend to use private cars. The majority of frequent ICT users are single or childless young adults with a good education in urban areas.[59]

[58] (Circella et al. 2012).

[59] (Rayle et al. 2016).

Women and parents of younger children in Great Britain suffer from social exclusion and being hard-pressed, mainly due to low physical access and less flexibility to telecommute.[60] They may become more flexible both temporally and spatially via virtual access and thus be more included socially.

[60] (Lavieri et al. 2018).

Urban and rural contexts can be hugely different, leading to varied physical access to certain activities. People living in higher density and mixed-use neighborhoods are less likely to engage in a shopping-trip chain during their commute because single-purpose shopping trips from home are so easy and efficient.[61] They tend to spend more time shopping both inside and outside homes and take more trip chains for shopping, but they travel shorter total distance and spend less time traveling for shopping purposes. The benefits of online shopping and delivery could be used to increase the efficiency of travel for people who live in low-density

[61] (Ferrell 2005).

neighborhoods. People can pick up their goods ordered online earlier at local drop-off and pick-up points for online purchases.[62]

[62] (Lee et al. 2017).

ICT can help disadvantaged populations gain more opportunities. Those elderly people who suffer from loneliness and are socially excluded by the digital divide can improve their lifestyle by gaining more access to information and reducing their gap with younger generations.[63] People with disabilities can benefit from AR because it will allow them to interact with the real world more efficiently. Smell, touch, hearing can be augmented via sensors. People who have visual disabilities may sense the sight by using audio cues and the hearing impaired can feel augmented hearing by using visual cues. However, it is evident that disadvantaged populations are still being left behind in this phase of the digital revolution. The main reason is that those ICT devices, especially those high-tech ones are sometimes not user-friendly for disadvantaged populations, or not popularized among them. For example, elderly people cannot get easy access to ICT devices compared with the younger generation, due to the rapid technological advancement. Older respondents were found to be less likely than younger generations to use AVs in European surveys.[64] It was reported that the proportion of those aged 80 years and above who are familiar with smartphones or the Internet is only 25.9% and that of those who do not use ICT at all is 38.5%. Elders may increase their interest in web-connect ICT devices when improvements are made according to their specific preferences, like longer time of the screen lock, fewer procedures for registration.

[63] (Schlomann et al. 2020).

[64] (Hudson et al. 2019).

Conclusions

ICT can not only modify people's lifestyles but also contribute to the modification and development of new patterns of travel behavior. How ICT integrated with travel behavior has been intensively discussed since the early 1990s, focusing on how different virtual activities affect travel choices. This led to a debate about substitution or complementarity effects, based on the analysis of telecommuting and teleshopping. Smartphones make people release spatial and temporal constraints, modifying or fragmenting activities anywhere and anytime.

Existing literature has investigated the relationship between physical and virtual access, establishing five main impacts of virtual

activities on location-based counterparts: substitution, complementarity, modification, fragmentation, and multitasking.

Next

Research gaps and challenges remain. First, virtual access research may overlook disadvantaged populations since they engage in fewer teleactivities than other groups do. Second, few studies have analyzed the interactions in a comprehensive way, attributed to the limitation of complex data collection. Few studies have taken variables like lifestyle preferences, awareness of/attitude towards ICT devices, and built environment into consideration.[65] Third, detailed studies about how virtual access impacts different user groups have not gained enough focus.

[65] (Ben-Elia et al. 2018).

Most of the above limitations are associated with data availability. Many data sets lack good information on the use of ICT devices, preventing researchers from developing more empirical analysis. Detailed panel data, like spatio-temporal travel data, demographic information data, and land use, are required to advance the understanding of travel-access relationships. Built environment attributes, such as locations where certain activities occur, self-reported diaries of virtual activities, and respondents' personal characteristics can enrich our research. Previous survey-based research needs to assume hypotheses about the interactions between virtual access and travel before collecting subjective answers while passive self-reported big data may be a good complement to discover fresh research questions. Big data can be more useful than traditional survey-based data sets since they can provide a dynamic evolution of people's activities and travel behaviors.

ICTs like smartphones are platforms for a large and diverse set of virtual activities, with widely disparate impacts on travel behavior. Most of our previous surveys cannot gather detailed information about all the apps, such as when and how long they are used. Recently, research on phone usage has been conducted to analyze people's ICT use by recording and capturing their virtual activities. Respondents were asked to download and set up a smartphone use tracking application to record their self-reported phone usage.[66]

[66] (Loid et al. 2020).

Along with the help of servers and algorithms, data scientists are making it possible to monitor an individual's travel behavior by providing time stamps and location information since smartphones are an integration of various sensors.[67] Although "big" passive data

[67] (Ettema and Verschuren 2007).

collection on app use can be of some help, we should also hold the view that they may not be able to provide information about respondents' physical and "offline" activities yet. Since big data are often biased,[68] these data generated by real-time tracking smartphones should be combined with interviews or surveys.[69]

[68] (Witlox 2015).

[69] (Schwanen and Kwan 2008).

New innovations like VR, AR, and AT are making virtual access more multifunctional. Physical activities may become much less fundamental and virtual access will completely change our lifestyles and travel behaviors as goods, services even personal interaction may become digitalized.

Further research should focus more on how newly-announced technologies affect travel behavior and how the five key effects of virtual activities (i.e., substitution, complementary, modification, fragmentation, and multitasking) vary depending on user group.

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